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THESIS

IMPROVING THE GOODNESS-OF-FITS ASSOCIATED WITH THE CURRENT AND PROPOSED COMBAT ACTIVE REPLACEMENT FACTORS (CARF) METHODOLOGY

by

Mario L. Solano

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Thesis Advisor: Chad W. Seagren
Second Reader: Thomas W. Lucas

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The U.S. Marine Corps developed the Combat Active Replacement Factor (CARF) methodology as a way to obtain reliable logistics planning factors to aid in the estimation of equipment losses in future conflicts. The continuous evaluation and validation of these types of methodologies is considered of critical importance, since its effects directly impact combat effectiveness, supply chain management, logistics, acquisitions, and overall budgeting. This thesis analyzes a proposed methodology for use in calculating Explicitly Calculated CARFs (ECCs), making use of real-world Master Data Repository (MDR) data from previous low- and medium-intensity conflicts. As well, this thesis analyzes proposed regression models used in calculating Federal Supply Code (FSC) and Federal Supply Group (FSG) CARFs. We employ bootstrapping techniques in order to analyze the sensitivity of ECCs and find that as many of 70% may exhibit extreme sensitivity to reasonable changes in usage data. We employ Ordinary Least Squares regression models to estimate CARFs by FSC and FSG and obtain dramatically more CARFs relative to the draft methodology. Finally, a cross validation of a sample of the regression models reveals that CARFs generated from such models tend to vary substantially from their actual values.

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IMPROVING THE GOODNESS-OF-FITS ASSOCIATED WITH THE CURRENT AND PROPOSED COMBAT ACTIVE REPLACEMENT FACTORS (CARF) METHODOLOGY

Mario L. Solano
Captain, United States Marine Corps
B.A., University of New Mexico, 2003

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March 2012

Author: Mario L. Solano

Approved by: Chad W. Seagren
Thesis Advisor

Thomas W. Lucas
Second Reader

Robert F. Dell
Chair, Department of Operations Research

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ABSTRACT

The U.S. Marine Corps developed the Combat Active Replacement Factor (CARF) methodology as a way to obtain reliable logistics planning factors to aid in the estimation of equipment losses in future conflicts. The continuous evaluation and validation of these types of methodologies is considered of critical importance, since its effects directly impact combat effectiveness, supply chain management, logistics, acquisitions, and overall budgeting. This thesis analyzes a proposed methodology for use in calculating Explicitly Calculated CARFs (ECCs), making use of real-world Master Data Repository (MDR) data from previous low- and medium-intensity conflicts. As well, this thesis analyzes proposed regression models used in calculating Federal Supply Code (FSC) and Federal Supply Group (FSG) CARFs. We employ bootstrapping techniques in order to analyze the sensitivity of ECCs and find that as many of 70% may exhibit extreme sensitivity to reasonable changes in usage data. We employ Ordinary Least Squares regression models to estimate CARFs by FSC and FSG and obtain dramatically more CARFs relative to the draft methodology. Finally, a cross validation of a sample of the regression models reveals that CARFs generated from such models tend to vary substantially from their actual values.

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LIST OF ACRONYMS AND ABBREVIATIONS

AAO	Approved Acquisition Objective
CARF LA	Combat Active Replacement Factors Low Assault
CARF LS	Combat Active Replacement Factors Low Sustainment
CARF MA	Combat Active Replacement Factors Medium Assault
CARF MS	Combat Active Replacement Factors Medium Sustainment
CARF	Combat Active Replacement Factor
CARF-STAT	CARF Statistical Analysis Tool
CEC	Combat Essential Code
Class VII	Type 1 End Items, Combat Essential
CI	Confidence Interval
CRC	Federal Supply Code Regression CARF
ECC	Explicitly Calculated CARF
FSC	Federal Supply Code
FSG	Federal Supply Group
FY	Fiscal Year
GRC	Federal Supply Group Regression
HIC	High-Intensity Conflict
LIC	Low-Intensity Conflict
MDR	Master Data Repository
MIC	Medium-Intensity Conflict
MMD	Median Maintenance Deadline
MTTL	Mean-Time-to-Loss
NIIN	National Item Identification Number
NOMEN	Nomenclature
NSN	National Stock Number
TAMCN	Table of Authorized Material Control Number
WIR	Recoverable Item Report (for USMC), without Intent to Repair

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EXECUTIVE SUMMARY

The Combat Active Replacement Factors (CARF) are logistics-planning factors that aid in the estimation of equipment losses in future conflicts. The continuous evaluation and validation of this methodology is critically important, since the CARF values are employed in the War Reserves System (WRS), where they directly impact combat effectiveness, supply chain management, logistics, acquisitions, and overall budgeting. Evaluating the effectiveness of these procedures is a meaningful area of study.

We begin with a comparative analytical review based on a sensitivity analysis of the currently proposed methods. Explicitly Calculated CARFs (ECCs) are factors calculated using available historical data, in this case, from Operation Iraqi Freedom and Operation Enduring Freedom, by observing the quantities of equipment deployed and the reported losses of such equipment during the years 2005 through 2010. We generate 50 bootstrapped replications of the historic usage data to obtain a distribution of ECCs for those items uniquely identified by Table of Authorized Material Control Numbers (TAMNs) with available usage data. We show that based on the individual level and phase of conflict, many ECCs are significantly sensitive to minimal changes in the data with which they are calculated. We find that 12 of the low level ECCs and 140 of the medium level ECCs are not significantly different from zero. The least sensitive were Assault ECCs for Low Intensity Conflict (ECC_LA), where 82 of 611 showed high sensitivity, while the most sensitive were Sustainment ECCs for Medium Intensity Conflict (ECC_MS), with 357 of 514 being highly sensitive.

The proposed methodology for calculating CARFs for equipment that do not have all the necessary information to obtain an ECC involves building linear regression models based on the equipment's classification within its hierarchy of the Federal Supply Code (FSC) and Federal Supply Group (FSG). These CARFs are denoted CRCs and GRCs, respectively. This leverages the assumption that similar end items, within the same classification, have similar attributes that can be used to calculate their attrition rate. We employ Ordinary Least Squares (OLS) regression and achieve vast improvements in terms of significance and model validity across the studied levels and phases of conflict,

relative to the draft methodology and we obtain a substantial increase in the number of CRCs and GRCs produced. For example, our method obtains 369 CRCs for the Assault phase of Medium Intensity Conflict (CRC_MA) and 398 GRCs for the Assault phase of Low Intensity Conflict (GRC_LA), relative to 2 and 46 according to the draft methodology.

We also cross-validate a sample of the regression models, with the primary intent to evaluate the performance of the regression fits and the hope of gaining some insight as to determining how sensitive the models would be to gaps in the data. In every trial, we withheld 20%, 15%, and 10% of the available data. With this, we could run the regression models and compare estimated CRC (or GRC) with the TAMCN's actual ECC as well as the bootstrapped Confidence Intervals. The examples we used here were the FSCs 2320 and 5820, and the FSG 23. These FSCs and FSG were chosen because of their amount of TAMCNs with available data and because of their primary importance, as rolling stock and communications equipment, to the operating forces. We find that even withholding 10% of the data upon which the original model was built produces results that tend to fall outside even the bootstrapped CIs.

Intending to provide an overall methodology that can predict over 6,000 CARF values based on the resulting values of the limited information on just 600 CARFs might not be the best approach. Though no validation was performed in the entire OLS process applicability and results, the conclusions obtained demonstrate the need for further research into proper methodologies.

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I. INTRODUCTION

A. MISSION AND PURPOSE OF THIS THESIS

This study's intent is to provide a comparative analytical review, based on a sensitivity analysis, of the proposed methods for forecasting equipment losses in future conflicts, known as Combat Active Replacement Factors (CARFs). This thesis, in a very narrow scope, will also aid in the future research of various proposed methodologies by reviewing multiple regression models that can be used in CARF value calculations.

The United States Marine Corps developed the CARF methodology as a way to obtain reliable logistics planning factors to aid in the estimation of equipment losses in future conflicts. The continuous evaluation and validation of this methodology is important since the CARF values are employed in the War Reserves System (WRS) and where they directly impact combat effectiveness, supply chain management, logistics, acquisitions, and budgeting.

CARFs are considered critical elements in the requirements determination process due to their effect on the entire Marine Corps' Acquisition Program. Funding requirements can be substantially altered with a small change in the CARF of either a "high-density or high-value dollar item" (Department of the Navy, 2010a, p. 1-5). The continued need to review the effectiveness of the procedures that derive these combat planning factors is a very attractive and meaningful area of study.

This thesis assesses the sensitivity of the results of the process for producing CARF estimates to reasonable changes in observed usage data. In addition, it maps out an alternative method for generating CARFs for items that lack usage data and it demonstrates a technique for evaluating the effectiveness of that method.

B. BACKGROUND

The CARFs have a crucial role in estimating the Marine Corps' War Reserve Materiel Requirements (WRMR) and feed into the Approved Acquisition Objectives (AAO). It is the responsibility of the Deputy Commandant for Installations and Logistics to validate CARFs and the methodology through which they are obtained, as per Marine

Corps Order (MCO) 5311.1D. CARFs reflect the anticipated combat replacement needed for equipment losses, on a 30-day basis, incident to amphibious operations and other combat operations (Department of the Navy, 2010b). As per MCO 5311.1D, a unit is considered to be in combat operations only when in direct enemy contact. Accurate CARFs provide the planning flexibility to meet requirements of any conflict, by theater and specific operational plan.

CARFs are an indispensable tool in determining War Reserve Materiel (WRM) stocks. NAVMC 4000.1 specifies that CARFs be established for Type 1 Principal End Items (Table of Authorized Material Control Number [TAMCN]) beginning with the letter A, B, C, D, or E) designated with a Combat Essential Code 1 (CEC 1), for Class II, clothing and individual item supplies, and Class VII, principal end item supplies, following the Plans, Policies, and Operations (PP&O) publication that contains the essential equipment list (Department of the Navy, 2010b). CARFs also have a direct impact on the strategic lift and sustainment requirements for a deploying Marine Air-Ground Task Force (MAGTF). These replacement factors are the planning guidelines used to properly equip forces in the specific phases, level, and duration of a conflict, in order to maintain quantities up to their Table of Equipment (T/E) level in the event that essential materiel is damaged beyond utilization during a contingency operation (Department of the Navy, 2010a).

CARFs are categorized in two phases of combat operations. The Assault Phase, represented by the first 30 days of combat, and the Sustainment Phase, represented by every subsequent 30-day period. The historical data used in calculating CARFs is, under a draft methodology proposition, categorized into three levels of conflict intensity:

- Low-intensity conflict (LIC): This level of intensity is described as a political-military confrontation between contending states or groups below conventional war and above the routine, peaceful competition among states. LICs are often localized, generally in third-world countries, but contain regional and global implications. A LIC can range from an insurrection to a more organized use of employing political, economic, informational, and military instruments, to include irregular warfare scenarios.
- Medium-intensity conflict (MIC): This level of intensity is perceived as a “protracted” employment of regular armies in

combat and a major manifestation of power by the opposing and responding nations, with the designation and prioritization of military objectives in order to achieve political and economic goals.

- High-intensity conflict (HIC): This level of intensity is described as a conflict in which we observe a relatively unconstrained use of power by one or more nations to gain or protect territory and interests that directly affect the survival of the nation. Extreme levels of violence and the employment of the full range of military forces are evident in this level of conflict (Draft version of a contracted 2011 study [Draft CARF Technical Report, 2011], 3).

The various CARFs to be obtained are shown in Table 1-1.

Table 1-1. CARF Values by Conflict Intensity and Phase (Draft CARF, 2011)

Intensity of Conflict	**Assault Phase**	**Sustainment Phase**
High Intensity Conflict (HIC)	CARF High Intensity Assault (CARFHA)	CARF High Intensity Sustainment (CARFHS)
Medium Intensity Conflict (MIC)	CARF Medium Intensity Assault (CARFMA)	CARF Medium Intensity Sustainment (CARFMS)
Low Intensity Conflict (LIC)	CARF Low Intensity Assault (CARFLA)	CARF Low Intensity Sustainment (CARFLS)

C. LITERATURE REVIEW

In early 1985, Professor Lindsay of the Naval Postgraduate School published a technical report titled *An Examination of the USMC Combat Active Replacement Factor (CARF) Determination System*. This report mentions the wide ongoing efforts that were conducted throughout the early 1980s to develop new procedures for the Marine Corps' CARF values generation, since until that decade only adapted Army replacement factor values were used. In his report, Lindsay compares two methods of estimating CARF values.

The first method relies on scenario-oriented models using mean-time-to-loss (MTTL) estimates and means of the observed distributions in different situations where specific items are subject to either the same loss rate or varying loss rates throughout a time period. Lindsay's report emphasizes that the use of exponential distributions to arrive at a time to loss is based on the same assumption of constant failure rates employed in reliability theory and, at that time, "essentially mandated" by the Department of Defense for this type of study (Lindsay, 1985).

The second method in this analysis looks at arriving at a CARF value based on the professional military judgment of many experts who rate "chance of loss" for specific types of equipment. Through this approach, a panel of subject matter experts (SMEs) is tasked with ranking the expected likelihood of loss of an item in various situations, and then compares which items should have a higher or lower CARF value. Those groups of rankings are converted into an interval scale, which can provide a scaled average score for each item and, in doing so, can provide CARF estimated values. As mentioned in Lindsay's report, the disadvantage observed with this methodology is the large number of SMEs needed in order to provide a sensible level of probability of success since it is "based upon the disagreement among judges" (Lindsay, 1985, p. 23). In his conclusions, Lindsay points out that, in certain instances, CARF values that are generated by relying on SME input might be the preferred approach since they often offer more substantial empirical evidence for the reasoning of the resulting values and the way they are obtained.

In December 1985, Major Hee Sun Song's (Republic of Korea Army) presented the results of his thesis research titled "Application of Life Distributions Estimated Equipment Losses in Combat," in which he proposed a similar CARF generation process based on MTTL estimates that can be applied to various types of life distributions, such as exponential, Weibull, or gamma, as well as to a nonhomogeneous Poisson process (Song, 1985). He suggests that CARFs generated is this manner are more sensible because it is easier to understand the thought process that brings about such input values and results.

The results of Song's thesis postulates that the intention to consider and compare all of these life distributions in the study of life expectancy of an item in a combat scenario aids in the proper selection of such a distribution, when one cannot be exactly identified because of the complexity of war scenarios in itself. Song also emphasizes that his work serves as an extension of Lindsay's work by " removing the need to assume a constant loss rate.“ (Song, 1985, p. 43) and suggests that it might be an easier approach if we consider different levels of combat intensity and calculate MTTLs for each with the intention that we avoid “sealing” all our estimations with one over-all-population MTTL. But, of note, in his conclusion he also states, “The choice of scenario and life distribution will, of course, depend primarily on the specific item being studied” (Song, 1985, p. 43).

In 1990, emphasizing the importance of having properly generated CARF values and their effects in the war reserves stock, Major Joseph L. Stylons, United States Marine Corps (USMC), publishes his findings in an NPS thesis titled “War Reserves Stocks and Marine Corps Sustainability.” He takes the approach of explaining how the “deficit-in-assertiveness” of our planning factors infect the proper war reserve stocks, the entire acquisitions program, and consequently the overall ability of the Marine Corps to project power as a global military force. The business point of view of this thesis reflects the wide ramifications of the matter of study to the overall funding levels and acquisition power and a definite need for emphasis in the use of these logistics planning factors (Stylons, 1990).

A review of the literature failed to identify any studies more recent than those discussed above, to include studies concerning other services.

D. AN EARLY VERSION OF A PROPOSED METHODOLOGY AND AVAILABLE DATA

A draft version of the study of a proposed Fiscal Year (FY) 2011 CARF assignment methodology follows a specific assignment algorithm decision flow map depicted in Figure 1-1.

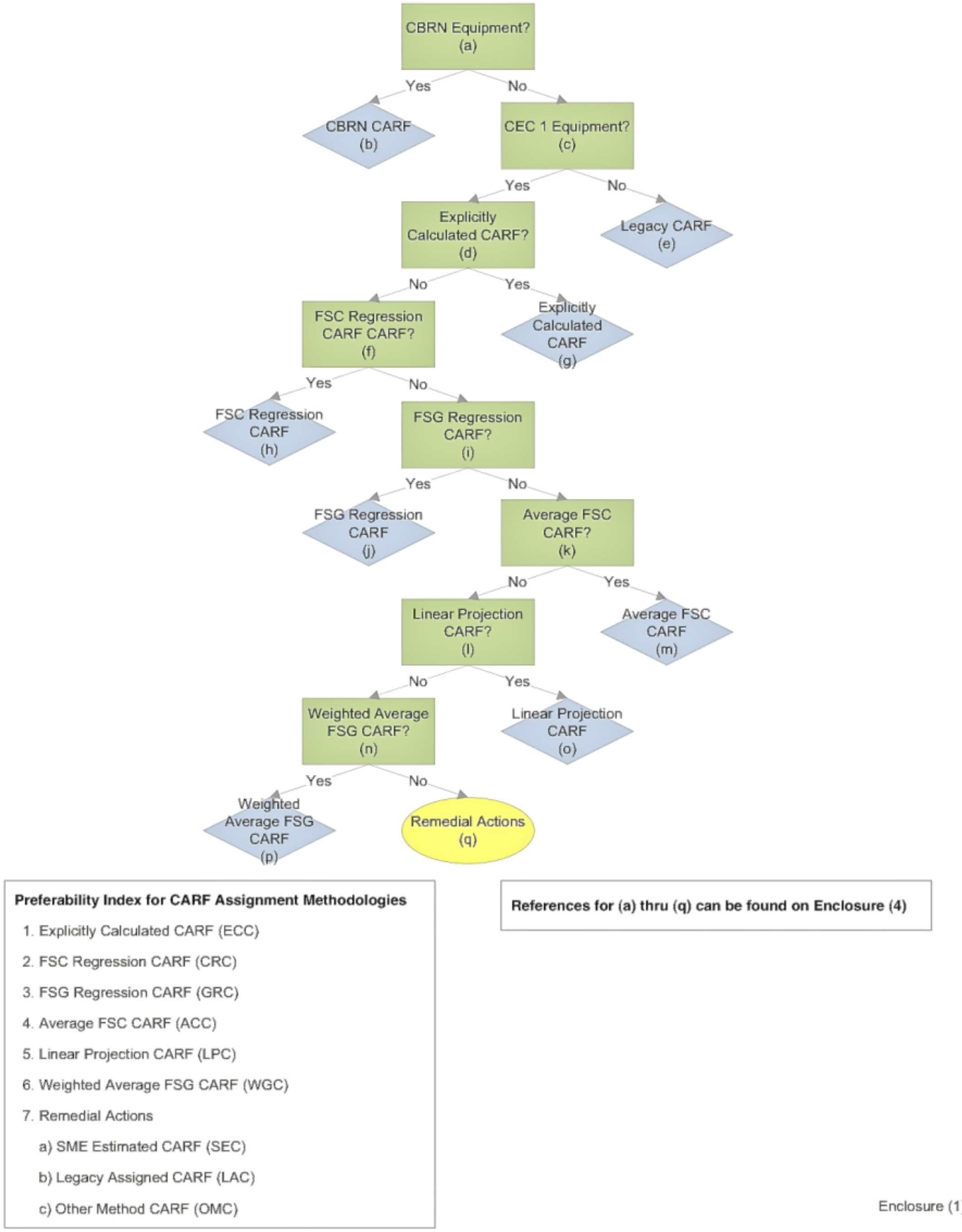

Figure 1-1. CARF Assignment Algorithm Decision Flow (LSX 2011).

This decision flow map encompasses a total of almost 7,300 calculated CARFs using different statistical models. Of the total CARFs, 15% are calculated by following an explicitly calculated CARF methodology and 14% are calculated using varying forms of regression models (Logistics Operations Research Branch [LSX], 2011).

In CARF assignment methodology, ECC values are calculated for those items, referred to as TAMCNs, with recorded data obtained from Operation Iraqi Freedom (OIF) and Operation Enduring Freedom (OEF) losses in low- and medium-intensity conflicts. Because of the lack of data, high-intensity conflicts require the use of combat modeling data and are outside of the scope of this thesis. This level of conflict is not considered in the methodologies reviewed in this study.

The two-phase categorization determines the inclusion of a Median Maintenance Deadline (MMD) factor added when calculating CARFs within the assault phase only, accounting for the temporary losses due to maintenance during this initial phase. This added factor is the arithmetic mean of the deadline time, per TAMCN, obtained from historical data from OIF and OEF (LSX, 2011).

In order to calculate a CARF over an assault or sustainment phase, for a specific TAMCN, the following essential pieces of information are needed: the number of days in the duration of the deployment, the total number of items deployed to the theater, the total number of items destroyed by date, and, for the assault period, the MMD. For example, using the equations first developed by the Marine Corps Combat Development Command, Operations Analysis Division, and described in the "Draft Combat Active Replacement Factors (CARFs) Technical Report" draft version of a 2011 study (LSX, 2011) a CARF calculated for the assault phase is obtained as follows:

$$Assault\ CARF = \left(\frac{K / N}{T} \times 30\ days \right) + MMD \quad .$$

where:

K = Total number permanently lost

N = Total number of items deployed

T = Total number days TAMCN was deployed to the contingency operation, and

MMD = Median Maintenance Deadline

In a CARF calculated for the sustainment phase, the following equation is used (LSX, 2011):

$$Sustainment\ CARF = \left(\frac{K/N}{T} \times 30\ days \right).$$

ECC methodology is the most accurate and preferred approach to calculating CARFs. Currently, 1,109 CARFs have been calculated using this ECC method (LSX, 2011).

For TAMCNs without sufficient information to calculate an ECC, the next step in the decision flow map is to calculate their CARFs by building a regression model from items within their same Federal Supply Code (FSC) that already have ECCs. These supply codes, and Federal Supply Groups (FSGs), represent National Stock Numbers (NSN), which are 13-digit numbers used by the Federal Government and assigned by the Defense Logistics Agency Customer Interaction Center (DLA CIC) to identify and classify products. For example, the first four digits of an NSN represent these FSCs and FSGs, which would contain similar groups of end items, i.e., NSN 2355-XX-XXX-XXXX represents the group of wheeled combat, assault, and tactical vehicles.

The type of model for estimating CARFs by FSC and FSG that we examine in this thesis is linear regression. However, it is important to note that the activity responsible for producing CARFs no longer uses linear regression as their preferred method. As specified in the Detailed CARF Assignment Methodology and CARF-STAT Documentation report (LSX, 2011) and in accordance with the legacy FY2011 CARF Assignment Algorithm, nested multivariate analysis techniques were used. Within the regression, two numerical predictors, total approved allowance and cost for a TAMCN, are selected as the most statistically significant and influential factors, based on the available data and the regression model that initially includes 23 terms. In this study of a proposed methodology, the resulting R-square obtained through this regression is 0.9843 (LSX, 2011), reflecting a sufficient goodness-of-fit for calculated CARFs.

For CARFs that cannot be calculated under a CRC method, the regression model is built on the next higher echelon of classification, the FSG. The FSG Regression CARF (GRC) method uses the attributes of the TAMCNs for which CARFs were obtained through the previous two higher levels, FSC and ECC. Once again, within the regression, the most statistically significant two numerical predictors remain the total approved allowance and the cost for a TAMCN (LSX, 2011).

E. PRELIMINARY OBSERVATIONS AND RECOMMENDATIONS ON HOW TO PROCEED

As a first approach, we bootstrap the historical usage data in order to perform a sensitivity analysis for the calculation of ECCs. We develop a criterion that describes the sensitivity of ECCs to changes in the usage data. We find that as many as 140 TAMCNs have ECCs so sensitive that their bootstrapped confidence intervals contain 0.0. In addition, we find that as many as 303 low-level conflict ECCs and 357 medium-level conflict ECCs that have valid confidence intervals may be overly sensitive.

As a second objective, we focus our efforts on the 1,137 CARFs in which FSC/FSG Regression CARF methodology is employed, by assessing the validity of each regression model presented. We are able to produce 14,292 CARFs using different regression models. In addition, we outline a method for assessing the validity of these CARF estimates.

Ultimately, our results show that caution is in order when applying statistical methods in an attempt to overcome the pervasive gaps in usage data. Given the relative paucity of usage data, and the sensitivity of parameters calculated from it, it is probably wise to consider at least augmenting the process with combat modeling and simulation and the contributions of subject matter experts.

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II. AVAILABLE DATA AND DETAILED CARF REGRESSION METHODOLOGY

A. PROVIDED DATA AND ITS EMPLOYMENT

The data for this study are contained in a table that covers information on 6,137 unique TAMCNs. As mentioned in a draft version of a contracted 2011 study (LSX, 2011), the JMP© statistical analysis toolset (see www.jmp.com) is used because of its commercial off-the-shelf availability and its ability to be easily employed for quick analysis and create multiple regression models. This file includes scripts for automatically calculating ECCs for low- and medium-intensity conflicts, to include the respective assault phases, based on usage data from Marine Expeditionary Forces (MEF) between 2005 and 2010 in OIF and OEF. The file also includes scripts for fitting FSC and FSG regression models, as well as further-on procedures that are depicted in the decision flow map, such as Average FSC CARF (ACC) and Weighted Average FSG CARF (WGC), which are not within the scope of this thesis.

The 6,137 rows represent each TAMCN, or individual equipment variant, that the MEFs employ, and capture a wide variety of information, such as dimensions, weights, commodity, nomenclature, NSNs, CECs, and weapons systems codes (see Appendix A for full data sample).

1. Table of Authorized Material Control Number (TAMCN)

The TAMCNs are the most expedient way to track the equipment variants while maintaining data integrity with the MDR source files provided. TAMCN5s only show the first five numbers of every one of these TAMCNs, which provides a grouping of similar TAMCNs. The first letter of a TAMCN refers to the commodity code, while the nomenclature (NOMEN) captures the assigned descriptive name of the equipment variant.

2. Combat Essential Codes (CECs)

CECs are designator numbers that indicate if the item is essential in a combat operation. As described in Chapter I, these CECs are assigned to equipment variants that have been identified as Combat Essential End Items and are classified as Type 1, Type 2, or Type 3. Type 1 end items are TAMCNs beginning with A, B, C, D, or E. The WMR Handbook states that when calculated CARFs are employed, they are only applied to "TAMCNs associated with Type 1 End Items for Class II and VII" (Department of the Navy, 2010a, et al., p. 1-5). In the data presented, only 2,421 items are combat essential, represented by a CEC number of "1," and 3,716 items are represented by a CEC number of "0" as noncombat essential.

3. Total Approved Acquisition Objective (AAO_TOTAL)

The total equipment approved quantities are captured under AAO_TOTAL, which is an aggregate of the quantities reported by each of the three MEFs, the WRM reserves, each of the worldwide regional Marine Forces Commands, and the three Maritime Prepositioning Squadrons (MPSs).

4. Equipment Variant Best Cost (BEST_COST)

The unit price of these equipment variants is also reported in this data file under the header BEST_COST, which is the greater value when comparing three costs in the data file: the cost to procure (COST_PROCURE), the cost to replace (COST_REPLACE), and the standard unit price (STD_UNIT_PRICE).

5. Dimensional Information

For most TAMCNs, physical dimensions such as weight, length, normal height and lowest height (i.e., motorized cranes), and width are included in the dataset all of these are factors that could be observed as possibly influential in a regression model.

6. Total Quantity On-Hand and Losses (OH and WIR)

Historical data, such as total quantity on-hand (deployed) and total losses reported from 2005 through 2010, are available for approximately 10% of the TAMCNs. The on-hand data available is titled OH_VII_MEF_20XX, in which the last digits refer to the year it covers. The dataset only provides observations for 908 TAMCNs for each of the six years of recorded data. The equipment losses are also accumulated by year under the headers WIR_VII_MEF_20XX and comprise a total of 984 available observations per year. These totals refer to the number of cells that contain information for the specific TAMCNs for which data is available, i.e., only reported equipment on-hand during that year and only reported losses, if any for that year, will appear.

The data in the total quantity on-hand and losses is employed in the calculation of ECCs, as described in Chapter I, and form the core of the first analytical steps of this thesis for the purpose of bootstrapping over the losses, while maintaining the total on-hand data constant. This allows multiple replications that conform to the characteristics of the original ECC data, while obtaining simulated losses to further study performance of the methodology. This process is further detailed in Chapter III.

Emphasis is placed on analyzing this first step of calculating ECCs. Since the calculated ECC will serve as a "seed" from where the rest of the decision "tree" is built upon, it is of keen importance to prove resiliency. We obtain a confidence interval that reflects how much we can rely on this initial step, which will grow the different "branches" that become the FSC, FSG, ACC, and WGC CARFs.

B. DESCRIPTION OF THE REGRESSION MODELS AND OBSERVATIONS

As detailed in Chapter I, a proposed CARF methodology uses regression analysis to build a predictive model in which CARF values are calculated for those individual equipment variants that do not have enough historical information for an ECC approach.

Equipment variants that fall within the same general end use are classified under the same FSC. Within each FSC, many TAMCNs may not have historical usage data available. The intent is to fit a regression to the TAMCNs within the FSC for which historical data is available, and use that model to predict a CARF for the TAMCNs that lack usage data. As with all regression models, the bigger the N, where N = number of TAMCNs with historical data, the more reliable and/or acceptable prediction we expect to encounter.

Both regression models assume that FSC and FSG assignments have been validated by the Marine Corps Combat Development Command (MCCDC) Integration Division (ID) and considered accurate (LSX, 2011). This is of relevance since the similarity between these assigned FSC and FSG classifications is something from which we can draw similarities in order to generalize the fitting of the employed regression models.

The 6,137 TAMCNs are classified in a total of 274 FSCs, which are categorized under a total of 63 FSGs. The breakdown of the total number of TAMCNs per FSG is presented in Table 2-1.

Table 2-1. Total Number (N) of TAMCNs by FSG

FSG	N	FSG	N	FSG	N	FSG	N
10	128	37	12	56	5	74	16
12	50	38	87	58	822	75	19
13	42	39	40	59	123	76	1
14	23	40	15	60	6	79	15
15	4	41	102	61	144	80	1
16	76	42	225	62	25	81	41
19	11	43	39	63	20	83	55
23	361	44	2	65	64	84	872
24	7	45	10	66	483	85	2
25	57	46	22	67	35	88	5
26	1	47	6	68	12	89	45
28	6	49	186	69	58	91	1
29	5	51	180	70	340	93	8
34	38	52	9	71	30	95	5
35	32	53	5	72	24	99	388
36	12	54	55	73	26		

An example of the use of these FSGs and FSCs, in a simplified view, is provided in Table 2-2. In the example, FSG 15 refers to the overall group of aircraft and airframe structural components. FSC 1550, drones, falls under this grouping category and includes four distinct TAMCNs, as presented in the table. The complete list of FSCs is presented in Appendix B.

Table 2-2. Example of FSG 15, FSC 1550, and TAMCNs Classification

FSG	FSC	TAMCN	NOMENCLATURE
15	-----	------------	AIRCRAFT AND AIRFRAME STRUCTURAL COMPONENTS
	1550	-----------	DRONES
		A01217G	MICRO UNMANNED AERIAL VEHICLE (MUAV)
		A03217G	DRONE ACFT, RAVEN DDL
		A32527G	UAV SYSTEM, DRAGON EYE
		A32527G	UAV SYSTEM, RAVEN

The regression model employed for the FSC CARF uses a Generalized Linear Model (GLM) regression with a Poisson distribution and a log-link function. The AAO_TOTAL and BEST_COST, and their first order interaction, are the regressors for each FSC. The regression models employed for the FSG CARF replicate this same procedure.

The early version draft CARF report justifies the use of the GLM regression by stating that its primary benefit is the ability to employ a "variety of distribution families and associated fit functions" (LSX 2011, pg 9) in order to capture the complexity of dependencies between the necessary regression factors. While unable to re-create the same results as presented by the draft CARF report, analyzing the results obtained when following the regression methodology reveals that none of these FSC regressions (CRCs) are valid. Most of them show an insufficient chi-square test result and—a most compelling observation—all of the parameter estimates' p-values are at or above a 0.9, indicating no real importance as far as being influential factors in the regression.

The decision flow map from the proposed CARF methodology, presented in Chapter I, indicates that previously obtained calculations for the FSC CARF, in conjunction with the previously calculated ECCs, are to be used in the FSG CARF regression models. This is not evident in the FSG CARF computational procedure and regression analysis script provided. In fact, the procedure is repeated and directly follows the same steps used in calculating FSC CARFs, regressing on AAO_TOTAL and BEST_COST and their first order interaction, the cross effect

AAO_TOTAL*BEST_COST, without making use of the successfully calculated ECCs and FSCs. This, in turn, would neglect the value added to the FSG regression as provided by previously calculated FSCs.

C. VISUALIZING CURRENT RESULTS OF THE PROPOSED CARF METHODOLOGY

The total count of CARFs assigned, by level and phase of conflict, using the ECC, CRC, and GRC procedures are depicted in Table 2-3. From the total of 6,137 TAMCNs, and only reporting on the 2,421 CEC 1 TAMCN, on average almost 31% of them have been assigned an ECC CARF; less than 5% have been assigned a CRC CARF; and less than 3% have been assigned a GRC CARF.

Table 2-3. Total CARFs Assigned with % of Total (ECC/CRC/GRC)

	ECC	% of Total	CRC	% of Total	GRC	% of Total
CARF LA	611	30.40	190	9.45	46	2.29
CARF LS	626	31.21	197	9.82	51	2.54
CARF MA	611	30.40	2	0.10	59	2.94
CARF MS	621	30.91	3	0.15	65	3.24

Figures 2-1 through 2-4 give a graphical representation of the number of CARFs assigned by all the procedures used in a proposed CARF methodology.

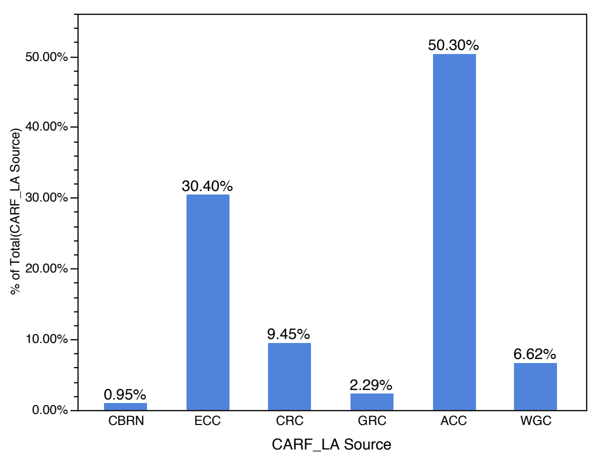

Figure 2-1. Obtained LA CARFs by Source.

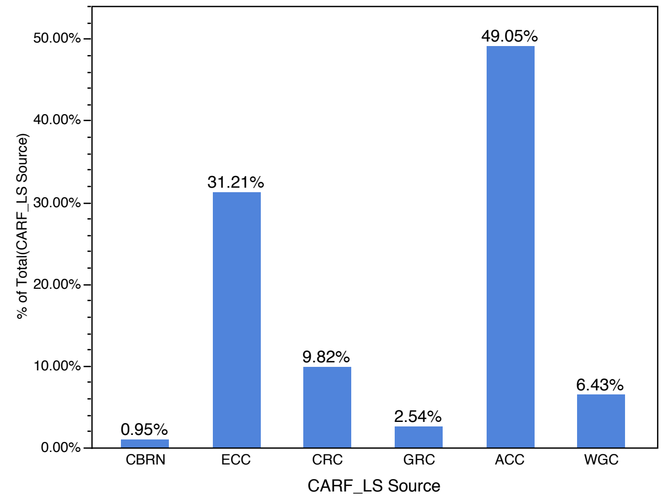

Figure 2-2. Obtained LS CARFs by Source.

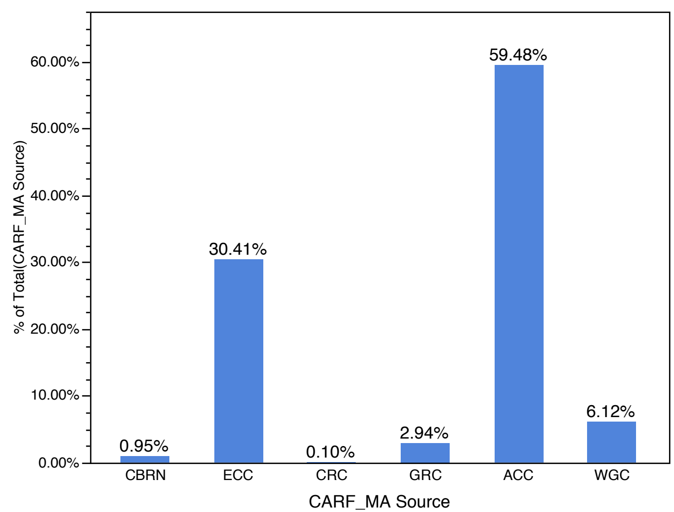

Figure 2-3. Obtained MA CARFs by Source.

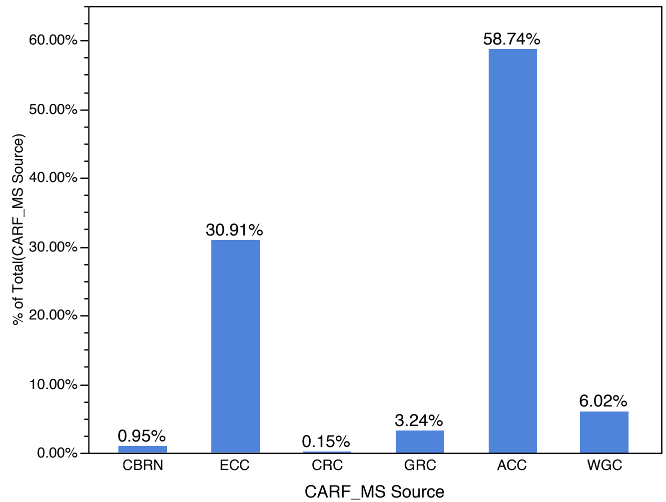

Figure 2-4. Obtained MS CARFs by Source.

Figures 2-1 and 2-2 depict the sources for the low-level conflict, the assault and sustainment phases, respectively. For the assault phase of this level of conflict over 9% of the CARFs are obtained by a CRC approach, while roughly 2% is obtained through a GRC approach. We can observe comparable results for the sustainment phase, where close to 10% is obtained by CRC and only 2.5% is obtained by GRC. The perception of this difference can be simply explained by understanding that the sustainment phase comprises more observed time and more data captured during that event.

In contrast, Figures 2-3 and 2-4 depict the sources for the medium-level conflict and show the overall inverse results. For the assault phase, a mere 0.10% is obtained through CRC, while 3% is obtained through GRC. Similarly, for the sustainment phase, 0.15% is obtained through CRC compared to over 3% by GRC. We can interpret this difference as a result of the evident contrast between a medium-level conflict, which has historically been of a shorter duration, and a low-level conflict. In this case, the scarceness observed in the available data in a medium-level conflict forces the employment of the FSG regression models (GRC) to be more frequently relied upon for CARF value calculations, thus generalizing loss quantities within an FSG.

Overall, the intention of increasing reliance on the regressed models employed in calculating CARF values arises from (1) the sparseness of the available historical data used in calculating ECCs, which demands a method that can fill those "gaps" with reliable CARF values; and (2) that most of the CARF values that are not currently obtained from a explicitly calculated approach, using the sparse data available, are obtained from other methodologies that depend upon the resiliency of the CRC and GRC methodology, as is the case of an ACC and the GRC (LSX, 2011). If historical data collection and management is bolstered, the regressed methodology can be further developed to serve as bedrock for a more resilient and accurate means of calculating equipment needs for the operating forces and overall acquisitions policies.

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III. BOOTSTRAPPING ON ECC CARF AND REGRESSION ANALYSIS OF FSC AND FSG CARF MODELS

A. BOOTSTRAPPING ON AVAILABLE HISTORICAL DATA FOR ECC SENSITIVITY ANALYSIS

CARFs are essentially an expected number of casualties in a future conflict per unit of equipment deployed in combat. The dataset contains the annual total equipment deployed and total casualties observed for approximately 740 TAMCNs. We obtain ECCs for each CARF for which there is usage data. Since the data are sparse and the proportion of casualties small, the ECCs may be highly sensitive to reasonable variation in the data. We test the extent to which the ECCs are overly sensitive to changes in the input data by bootstrapping 50 additional datasets. Unless otherwise indicated, all TAMCNs refer only to CEC 1 items.

1. Bootstrapping

For a given TAMCN with a particular number of units deployed to a combat zone, the number of casualties can be modeled as a binomial distribution. Each day represents an opportunity for each piece of equipment to experience a casualty, thus complying with the assumption of a fixed number of trials. We assume independence between trials and constant probability of failure. Thus, the number of casualties for a given TAMCN for a particular year is distributed binomially, as follows:

$$casualties \sim BINOM\left(\left(n = Total\,on\,hand \times 365\,days\right), \left(p = \frac{x}{n}\right)\right),$$

where x is the total number of casualties observed for that year and 365 days of the year representing 365 opportunities for the total deployed number of TAMCNs to fail.

In performing this sensitivity analysis, the bootstrapping methodology is applied to the equipment losses (WIR_VII_MEF_20XX) for the years 2005 thru 2010. These data are extracted and placed in a Microsoft Excel file to be used as an input file for a JAVA script to more efficiently perform the necessary functions, using a random number generator to obtain the results. Fifty replications of this procedure are performed generating a total of 306,850 rows of bootstrapped data available once all replications are stacked. We then run the original ECC script on the bootstrapped dataset in order to obtain a distribution of ECCs for each TAMCN.

We obtain a 90% bootstrapped confidence interval for each TAMCN that was originally assigned an ECC. We observe the following: Of the 611 ECC_LAs and 611 ECC_MAs, 12 TAMCNs have bootstrapped confidence intervals that contain 0.0. Of a total of 626 ECC_LSs, 135 have bootstrapped confidence intervals that contain 0.0. Of the total of 626 ECC_MSs, 140 have bootstrapped confidence intervals that contain 0.0.

We are able to identify the problem that creates these results by observing that in the numbers reported in the original file presented for the study of this thesis, the casualties reported under the column headers WIR_VII_MEF_2XXX, as defined in Chapter II, have very sparse data. The lack of information for losses in these specific TAMCNs, throughout the years reported, create a problematic "noise" that can affect the calculations used in producing valid ECCs and regression predicted values. In Table 3-1, the 12 ECC_LAs and MAs that have a lower bound of 0.0 are presented together with their cost, emphasizing the impact unreliable ECC values can have for some of these TAMCNs.

Table 3-1. FSCs with ECC_LAs and MAs with 90% Bootstrapped Confidence Intervals that Contain 0.0

FSC	**TAMCN**	**NOMENCLATURE**	**Interval Lower Bound**	**Interval Upper Bound**	**Item Cost ($)**
6930	A70467G	GENERATOR, SIGNAL	0	0.0036	18,500
6930	A70467G	GENERATOR, SIGNAL	0	0.0040	17,520
6930	A70467G	40 GHZ SIGNAL GENERATOR	0	0.0040	17,520
6930	A70527G	1 GHZ SIGNAL GENERATOR	0	0.0011	10,083
6930	A70597G	SOIL RESISTIVITY TESTER	0	0.0004	2,367
6930	A70847G	LOCAL AREA NETWORK TEST SET	0	0.0019	7,116
6930	A70847GA	ANALYZER, NETWORK	0	0.0021	10,481
8110	B05717B	DRUM, FABRIC, COLLAPSIBLE, 500 GAL. CAP.	0	0.0012	2,088
8110	B05717B	DRUM, FABRIC, COLLAPSIBLE, 500 GAL. CAP.	0	0.0011	2,128
5180	B22602E	TOOL KIT, PIONEER, ENGR SQUAD	0	0.0007	3,193
5180	B22602E	PIONEER KIT (SQD)	0	0.0009	10,000
4933	E05002E	KIT, GAUGE, PULLOVER, COMPLETE	0	0.0037	2,927

In Table 3-2, only the 10 highest-cost items for ECC_LS and ECC_MS with a lower bound of 0.0 are presented. The complete list of these particular TAMCNs is presented in Appendix C. Also, their cost is included in Table 3-2 to emphasize the severity that these inconsistencies on obtained ECCs can have on some TAMCNs. These 10 TAMCNs are items with a unit cost exceeding $1 million.

Table 3-2. Sample of FSCs with ECC_LSs and MSs with 90% Bootstrapped Confidence Intervals that Contain 0.0

FSC	TAMCN	NOMENCLATURE	Interval Lower Bound	Interval Upper Bound	Item Cost ($)
B00157B	2330	Z BACKSCATTER RUGGEDIZED TRAILER (ZBRT)	0	0.0075	72,080,000
E08567K	2350	ASSAULT AMPHIBIOUS VEHICLE, RECOVERY	0	0.0486	4,054,968
E13787K	2350	RECOVERY VEHICLE, FT, HEAVY, W/EQUIP	0	0.0679	2,400,000
A21797G	5820	TERMINAL, RADIO, TROPOSCATTER, DIGITAL	0	0.0125	1,500,000
A21797G	5820	TERMINAL, RADIO, TROPOSCATTER, DIGITAL	0	0.0153	1,500,000
A21797G	5820	TERMINAL, RADIO, TROPOSCATTER, DIGITAL	0	0.0153	1,500,000
A23067G	2355	GROUND SENSOR SURVEILLANCE VEHICLE (GSSV)	0	0.0465	1,500,000
A04997G	5895	DIGITAL TECHNICAL CONTROL (DTC) FACILITY	0	0.0253	1,213,000
A04997G	5895	DIGITAL TECHNICAL CONTROL (DTC) FACILITY	0	0.0379	1,213,000
A21797G	5820	TERMINAL, RADIO, TROPOSCATTER, DIGITAL	0	0.0176	1,000,000

The same inaccuracy in the calculated ECC CARF values is observed for the rest of the 140 ECC_MSs and the 12 ECC_LSs. Thus, the CARFs generated for a non-trivial number of TAMCNs are not significantly different from zero. Some of the CARFs affected include extremely high dollar value items, which means making allowancing decisions on ultimately unreliable CARF estimates could prove costly.

2. Sensitivity Criteria Explained

Because implications such as authorized allowance decisions and materiel acquisitions can be based on these CARF values, it is necessary to identify the range of unacceptable values of the ECC estimates. We measure what we call a sensitivity ratio to more effectively analyze the deviance from an acceptable range of values. Let the 90%

bootstrapped confidence interval for a particular TAMCN be given by $[L,U]$, where L represents the lower limit and U represents the upper limit. Then, the sensitivity ratio is given by:

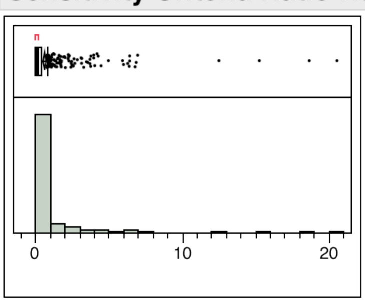
$$Sensitivity\,Ratio = \left(\frac{U-L}{L}\right).$$

With this sensitivity ratio calculation, a resulting value of 1.0 or greater suggests the upper bound is twice the lower bound. We have deemed all CARF_ECCs with Sensitivity Ratios exceeding 1.0 as unacceptable. However, this subjective decision is ultimately up to the relevant decision maker, as such wide ranges may impact allowancing and budgeting decisions.

a. ECC_LA

For the low level of conflict and in the assault phase, a total of 611 ECC_LAs have enough data to observe a sensitivity ratio analysis. Figure 3-1 shows the distribution of the sensitivity ratios for the ECC_LAs. Of the 611 TAMCNs with ECC_LAs, 82 (13%) have sensitivity ratios equal to or greater than 1.0. The maximum sensitivity ratio is 20.6.

Sensitivity Criteria Ratio Results Distribution for ECC_LA



Quantiles

100.0%	maximum	20.5978
99.5%		15.1397
97.5%		4.44096
90.0%		1.55265
75.0%	quartile	0.3322
50.0%	median	0.13484
25.0%	quartile	0.03876
10.0%		0.01795
2.5%		0
0.5%		0
0.0%	minimum	0

Moments

Mean	0.6105306
Std Dev	1.7102032
Std Err Mean	0.0691874
Upper 95% Mean	0.746405
Lower 95% Mean	0.4746561
N	611

Figure 3-1. Sensitivity Ratio Interval Distribution for ECC_LA TAMCNs.

Only a sample of the top ECC_LA TAMCNs, and the FSCs they fall under, are presented in Table 3-3, for those that reach the highest number greater than 1.0 when analyzing the resulting sensitivity ratio. These high values of resulting sensitivity are meaningful in that they represent those ECC values that are extremely sensitive to minimal data variations. This makes the ECC values very unreliable, in terms of their employment in proper calculations for any sort of regression fits and analysis. The nomenclature is included in these tables to emphasize the diversity of equipment that can be affected.

Table 3-3. Sample of the Top 10 of ECC_LA CARF FSCs Failing Sensitivity Ratio

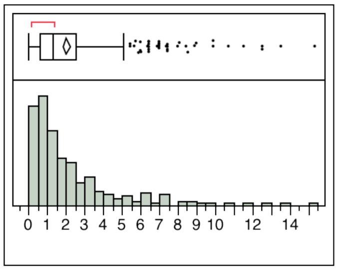
FSC	TAMCN	NOMENCLATURE	Interval Lower Bound	Interval Upper Bound	Sensitivity Criteria Ratio
2355	A23067G	GROUND SENSOR SURVEILLANCE VEHICLE	0.0005	0.0102	20.600
2355	A23067G	SENSOR SYSTEM, MONITOR, MOBILE	0.0005	0.0093	18.710
5810	A80447G	LIMITED MAINT SPARE PARTS KIT	0.0002	0.0036	15.310
6930	A70847G	ANALYZER, NETWORK	0.0002	0.0024	12.550
8145	C44332E	CONTAINER, QUADRUPLE (QUADCON)	1e-5	0.0001	7.000
6930	A70847G	LOCAL AREA NETWORK TEST SET	0.0003	0.0026	6.900
2350	E00357K	KIT, ARMOR, APPLIQUE	0.0301	0.2356	6.826
8145	C44332E	CONTAINER, QUADRUPLE (QUADCON)	1e-5	0.0001	6.450
8145	C44332E	CONTAINER, QUADRUPLE (QUADCON)	1e-5	0.0001	6.450
2590	E09967M	BLADE, MINE CLEARING	0.0030	0.0225	6.422

The severity of the impact of these highly sensitive ECCs, identified in Table 3-3, can be also emphasized by the TAMCNs' cost. The highest-priced items are listed in Table 3-3. Topping this list is the case of TAMCN A23067G, Ground Sensor Surveillance Vehicle, at $1.5 million, together with its respective Mobile Sensor Monitor System with a cost of $657,000.

b. ECC_LS

For the low level of conflict and in the sustainment phase, of a total of 519 ECC_LSs, 303 (58%) have a sensitivity ratio equal to or greater than 1.0. This means that more than half of the available ECC_LSs could be considered extremely sensitive to small fluctuations in the data provided for its calculations. Figure 3-2 shows the distribution of sensitivity ratios. The values can reach as high as a maximum of 15.36.

Sensitivity Criteria Ratio Results Distribution for ECC_LS



Quantiles

100.0%	maximum	15.3636
99.5%		12.9455
97.5%		8.45
90.0%		4.5
75.0%	quartile	2.51648
50.0%	median	1.2654
25.0%	quartile	0.59052
10.0%		0.27202
2.5%		0.15549
0.5%		0
0.0%	minimum	0

Moments

Mean	2.0098763
Std Dev	2.1990428
Std Err Mean	0.0965273
Upper 95% Mean	2.1995093
Lower 95% Mean	1.8202432
N	519

Figure 3-2. Sensitivity Ratio Interval Distribution for ECC_LS TAMCNs.

The TAMCNs with the 10 highest sensitivity ratios are presented in Table 3-4. TAMCNs with high sensitivity ratios are extremely sensitive to minimal data variations. With the nomenclature included in the table, we can observe equipment that is critical to the operating forces and combat operations.

Table 3-4. Sample of the Top 10 of ECC_LS CARF FSCs Failing Sensitivity Ratio

FSC	TAMCN	NOMENCLATURE	Interval Lower Bound	Interval Upper Bound	Sensitivity Criteria Ratio
3805	B00637B	TRACTOR, RUBBER TIRE, ARTICULATED STEERING, MP	0.0002	0.0034	15.360
6150	B05797B	DUMMY LOAD, GENERATOR SET, ELECT, 100KW, TRLR-MTD	0.0003	0.0042	13.550
6930	A70847G	ANALYZER, NETWORK	0.0002	0.0024	12.550
2320	D10627K	TRUCK, CARGO, 7 TON, XLWB, W/WINCH	0.0003	0.0037	12.550
5855	E19477B	TEST SET, NIGHT VISION	0.0013	0.0161	11.550
4930	B11357B	REFUELING SYSTEM, EXPEDIENT, HELO	0.0016	0.0186	10.730
2320	D08867K	TRUCK CARGO ARMOR 22.5 TON, 10X10, (LVSR)	0.0004	0.0047	9.909
2410	B24607B	TRACTOR, FT, W/ANGLE BLADE	0.0002	0.0024	9.909
6150	B05797B	DUMMY LOAD, GENERATOR SET, ELECT, 100KW, TRLR-MTD	0.0005	0.0052	9.000
2355	E09467B	LAV, COMMAND AND CONTROL (BN)	0.0047	0.0140	2.000

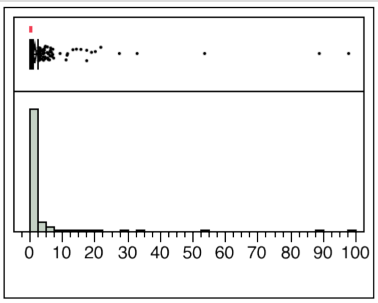
Among the sample of identified highly sensitive ECCs in Table 3-4, the highest-value item is TAMCN E09467B, Command and Control LAV, with a cost of $3.25 million.

c. ECC_MA

For the medium level of conflict, in the assault phase, of a total of 611 ECC_MAs, 176 have a ratio equal to or greater than 1.0. Almost 30% of the available ECC_MAs can be considered extremely sensitive to small fluctuations in the data provided for their calculations.

Figure 3-3 shows the distribution of sensitivity ratios. The values can reach an extreme maximum of 98, which is indicative of a very unreliable ECC.

Sensitivity Criteria Ratio Results Distribution for ECC_MA



Quantiles

100.0%	maximum	98
99.5%		52.5695
97.5%		11.5053
90.0%		2.93435
75.0%	quartile	1.12283
50.0%	median	0.40671
25.0%	quartile	0.13884
10.0%		0.05747
2.5%		0
0.5%		0
0.0%	minimum	0

Moments

Mean	1.6626515
Std Dev	6.4156449
Std Err Mean	0.2595492
Upper 95% Mean	2.17237
Lower 95% Mean	1.152933
N	611

Figure 3-3. Sensitivity Ratio Interval Distribution for ECC_MAs TAMCNs.

A sample of the 10 TAMCNs with the highest sensitivity ratios are presented in Table 3-5. As for the ECC_LAs and ECC_LSs, TAMCNs with high sensitivity ratios are extremely sensitive to minimal data variations.

Table 3-5. Sample of the Top 10 of ECC_MA CARF FSCs Failing Sensitivity Ratio

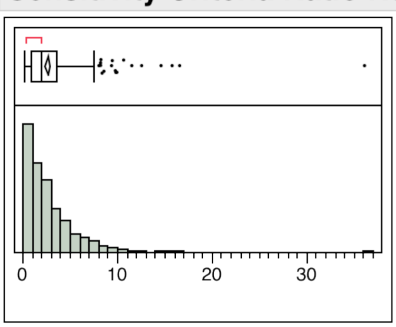
FSC	TAMCN	NOMENCLATURE	Interval Lower Bound	Interval Upper Bound	Sensitivity Criteria Ratio
2355	A23067G	GROUND SENSOR SURVEILLANCE VEHICLE	0.0005	0.0469	98.00
2355	A23067G	SENSOR SYSTEM, MONITOR, MOBILE	0.0005	0.0427	89.00
5810	A80447G	LIMITED MAINT SPARE PARTS KIT	0.0002	0.0121	53.81
5855	E19097B	TEST SET, BORESIGHT COLLIMATOR	0.0024	0.0806	33.10
5820	A00757G	ARCHIVED TAMCN	0.0001	0.0026	27.66
1240	E17802E	SIGHT, BORE, MORTAR, W/CASE	0.0003	0.0063	21.96
5820	A21717GL	RADIO SET, VEHICULAR	0.0006	0.0124	20.27
1240	E17802E	SIGHT, BORE, MORTAR, W/CASE	0.0003	0.0056	19.10
5820	A21717G	RADIO SET, VEHICULAR	0.0006	0.0109	17.63
5820	A21717GK	RADIO SET, VEHICULAR	0.0006	0.0109	17.63

Among the samples of identified highly sensitive ECC_MAs in Table 3-5, the highest-value item is also TAMCN A23067G, Ground Sensor Surveillance Vehicle, with a cost of $1.5 million.

d. ECC_MS

Finally, for the medium level of conflict and in the sustainment phase, of a total of 514 ECC_MSs, 357 have a sensitivity ratio equal to or greater than 1.0. Figure 3-4 shows the distribution of sensitivity ratios. The values can reach a maximum of 36.2.

Sensitivity Criteria Ratio Results Distribution for ECC_MS



Quantiles

100.0%	maximum	36.165
99.5%		16.182
97.5%		8.74596
90.0%		5.75643
75.0%	quartile	3.59364
50.0%	median	1.88405
25.0%	quartile	0.81114
10.0%		0.44747
2.5%		0.29168
0.5%		0.14417
0.0%	minimum	0.12739

Moments

Mean	2.6068909
Std Dev	2.7813103
Std Err Mean	0.1226783
Upper 95% Mean	2.8479047
Lower 95% Mean	2.3658772
N	514

Figure 3-4. Sensitivity Ratio Interval Distribution for ECC_MSs TAMCNs.

The TAMCNs with the 10 highest sensitivity ratios for ECC_MSs are presented in Table 3-6. In addition, TAMCNs with high sensitivity ratios are extremely sensitive to minimal data variations. Their close resemblance to the TAMCNs depicted in Table 3-2 for the results of ECC_LSs is evident.

Table 3-6. Sample of the Top 10 of the ECC_MS CARF FSCs Failing Sensitivity Ratio

FSC	TAMCN	NOMENCLATURE	Interval Lower Bound	Interval Upper Bound	Sensitivity Criteria Ratio
2320	D10627K	TRUCK, CARGO, 7 TON, XLWB, W/WINCH	0.0006	0.0215	36.170
2320	D10627K	TRUCK, CHASSIS, XLWB, 7 TON, W/WINCH	0.0011	0.0185	16.640
6930	A70847G	ANALYZER, NETWORK	0.0008	0.0129	15.850
3805	B00637B	TRACTOR, RUBBER TIRE, ARTICULATED STEERING, MP	0.0004	0.0055	14.680
2320	D10627K	TRUCK, RTAA, CHASSIS, XLWB, 7 TON, W/WINCH	0.0011	0.0143	12.630
2410	B24607B	TRACTOR, FT, W/ANGLE BLADE	0.0011	0.0141	11.590
2430	B24627B	TRACTOR, FT, MEDIUM (CATERPILLAR)	0.0026	0.0302	10.730
2320	D08867K	TRUCK CARGO ARMOR 22.5 TON, 10X10, (LVSR)	0.0005	0.0050	9.909
2355	E09467B	LAV, COMMAND AND CONTROL (BN)	0.0167	0.0632	2.780
2355	E09477M	LAV, LIGHT ASSAULT, 25MM	0.0065	0.0179	1.750

Specifically, we can see TAMCN E09467B, the Command and Control LAV, as the highest-value item, with a cost of $3.25 million, followed by TAMCN E09477B, the Light Assault LAV, with a cost of $3.22 million.

While some of the FSCs represented in these tables refer to items of low-cost value, certain TAMCNs are essential combat assets of elevated monetary value in which an extreme sensitivity to minimal changes, identified in their ECC calculations, can have a harmful impact on the operating forces. Caution is also strongly emphasized since some of these high-dollar-value items affected by such small fluctuations in the available data may have elevated and widespread effects on the overall acquisition authorized allowances.

Bootstrapping over the losses provides an example of a possible way to test sensitivity of calculations based on relatively limited usage data. By creating a test, or confidence interval we can provide a metric that can be used to compare the original historical data values presented and the predicted values obtained from methodology calculations. In this case, the results reveal that there is more sensitivity to small fluctuations to data values in the sustainment phases than there is in the assault phases. This points to the observation that the existence of usage data does not necessarily ensure robust ECCs.

B. ANALYZING COMPATABILITY OF CURRENT FSC AND FSG REGRESSION MODELS

We were unable to replicate the Poisson regression models implemented in the legacy method for building FSC and FSG regression models. The sample of this regression model for an given FSC (FSG) is given by:

$$Log_e(CARF\,ECC\_XX) = \beta_o + \beta_1(AAO\_TOTAL) + \beta_2(BEST\_COST) + \beta_3(AAO\_TOTAL * BEST\_COST),$$

and is applied to every level and phase of conflict, i.e., ECC_LA, ECC_LS, etc.

Because there are 155 FSCs, less than 49 FSGs, and as many as four regression models to build for each, constructing these models in JMP is highly inefficient and tedious. We import the data into SAS (see www.sas.com), build the regression models, and achieve a more efficient way to observe results.

1. FSC Regression

With the current FSC regression CARF (CRC) methodology we observe results that were inconsistent with a properly fitted model. We fit a GLM using a Poisson distribution and a log link function. Our response variable is ECC_XX and the covariates are AAO_TOTAL, BEST_COST and AO_TOTAL*BEST_COST. For these, none of the Chi-Square tests are sufficient; most of the resulting F-statistics are greater than 0.9; and none of the p-values for any of the parameter estimates and their interactions are less than 0.5, with most of them remaining above 0.7. These are symptoms of a poorly fitted model in which the distribution is wrongfully determined for its proper employment, rendering the resulting models invalid.

We present an example of the GLM fit model results in an attempt to replicate the methodology suggested in the draft version of a contracted 2011 CARF study. This example is for FSC 2320, mostly rolling stock, i.e., MTVR 7-ton, refuelers, many HMMWV variants, etc., and comprising a total of 181 different TAMCNs. The results in this section are only for the response variable ECC_LA and are presented in Figure 3-5.

The rest of the results for response variables ECC_LS, ECC_MA, and ECC_MS can be found in Appendix D. A sample of the complete resulting files for the rest of the FSCs can be found in Appendix E (SAS Excel file). The complete electronic file can be made available on request.

Generalized Linear Model Fit FSC=2320

Response: ECC_LA
Distribution: Poisson
Link: Log
Estimation Method: Maximum Likelihood
Observations (or Sum Wgts) = 84

Whole Model Test

Model	-LogLikelihood	L-R ChiSquare	DF	Prob>ChiSq
Difference	0.17655182	0.3531	3	0.9498
Full	13.874747			
Reduced	14.0512988			

Goodness Of Fit Statistic	ChiSquare	DF	Prob>ChiSq
Pearson	1.1301	80	1.0000
Deviance	1.1236	80	1.0000

AICc
36.2558

Effect Tests

Source	DF	L-R ChiSquare	Prob>ChiSq
AAO_TOTAL	1	0.1814729	0.6701
BEST_COST	1	0.0024058	0.9609
AAO_TOTAL*BEST_COST	1	0.0449193	0.8322

Parameter Estimates

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq	Lower CL	Upper CL
Intercept	-2.90543	1.1292597	5.5141082	0.0189*	-5.55397	-0.524541
AAO_TOTAL	-8.232e-6	0.0000215	0.1814729	0.6701	-8.253e-5	2.225e-5
BEST_COST	-2.375e-7	4.8426e-6	0.0024058	0.9609	-1.121e-5	1.1766e-5
(AAO_TOTAL-21504.7)*(BEST_COST-201152)	5.207e-11	2.438e-10	0.0449193	0.8322	-3.49e-10	3.865e-10

Studentized Deviance Residual by Predicted

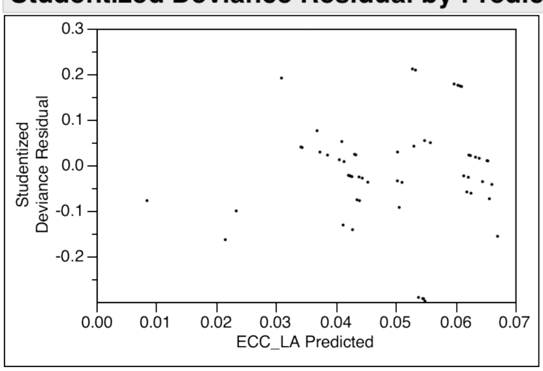


Figure 3-5. GLM Fit for CARF FSC 2320 Y=ECC_LA.

From the JMP output presented in Figure 3-5, we observe less than optimal results, where the effects test and parameter estimates show p-values 0.6701 for AAO_TOTAL, 0.9601 for BEST_COST, and 0.832 for AAO_TOTAL*BEST_COST. All remaining figures show the numeric significance predictors at similar and less than optimal results.

Table 3-7 summarizes the results and presents the number of valid models obtained in the previously mentioned FSC CARF methodologies, where a valid model is one that has at least one statistically significant term with a p-value of less than 0.1. None of these responses are valid models.

Table 3-7. Number of Valid Models in CARF FSC Regression (CRC)

Model Described	Number of Valid Models Generated from Total	Total Number of Models with Data Available for Analysis
Original CRC LA	0	58
Original CRC LS	0	87
Original CRC MA	0	58
Original CRC MS	0	87

2. FSG Regression

Similar results are observed for the current FSG regression CARF (GRC) methodology, where inconsistency remains indicative of a poorly fitted model as a result of using a Poisson distribution, a GLM personality with a log link function, the AAO_TOTAL, BEST_COST, and the interaction AAO_TOTAL*BEST_COST as the influential terms or numeric predictors. All Chi-Square tests are insufficient, the resulting F-statistics are greater than 0.9, and none of the p-values for any of the parameter estimates and their interactions show less than 0.5, with most of them remaining well above 0.7. These, as well, are symptoms of improperly fitted and invalid models.

An example of the GLM fit model results for FSG 12, Fire Control Equipment, which comprises a total of 22 different TAMCNs, of which only seven have ECCs, is presented in Figure 3-6 and, as in the previous example, only the results for response variable ECC_LA are presented. The rest can be found in Appendix F for response variable ECC_LS, ECC_MA and ECC_MS. A sample of the complete resulting files for the rest of the FSGs can also be found in Appendix G (SAS Excel file). The complete electronic file can be made available on request.

Generalized Linear Model Fit FSG=12

Response: ECC_LA
Distribution: Poisson
Link: Log
Estimation Method: Maximum Likelihood
Observations (or Sum Wgts) = 7

Whole Model Test

Model	-LogLikelihood	L-R ChiSquare	DF	Prob>ChiSq
Difference	0.00318211	0.0064	3	0.9999
Full	0.09718339			
Reduced	0.1003655			

Goodness Of Fit Statistic	ChiSquare	DF	Prob>ChiSq
Pearson	0.0019	3	1.0000
Deviance	0.0020	3	1.0000

AICc
28.1944

Effect Tests

Source	DF	L-R ChiSquare	Prob>ChiSq
AAO_TOTAL	1	0.0005542	0.9812
BEST_COST	1	0.0013269	0.9709
AAO_TOTAL*BEST_COST	1	0.0015711	0.9684

Parameter Estimates

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq	Lower CL	Upper CL
Intercept	-4.359791	72.278841	0.0041525	0.9486	-1486.12	886.10571
AAO_TOTAL	-0.000086	0.0035757	0.0005542	0.9812	-0.056701	0.0642424
BEST_COST	0.0006023	0.016238	0.0013269	0.9709	-0.259278	0.2757727
(AAO_TOTAL-24338.9)*(BEST_COST-6889.45)	-2.757e-8	6.8369e-7	0.0015711	0.9684	-1.111e-5	1.0654e-5

Studentized Deviance Residual by Predicted

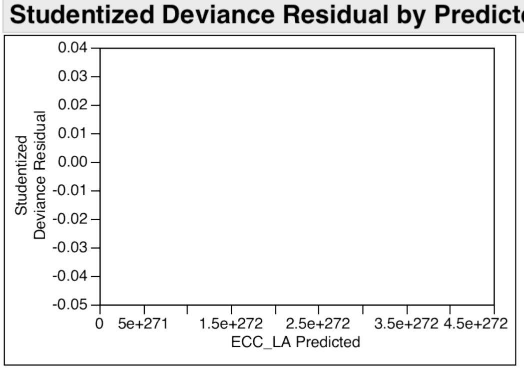


Figure 3-6. GLM Fit for CARF FSG 12 with Y=ECC_LA.

From the JMP output presented in Figure 3-6, we can observe the same less than optimal results in the FSG 12 GLM regression. Here, the effects test and parameter estimates show p-values above 0.95 for all numeric predictor terms. Similar invalid results are observed for the rest of the GLM regressions for this FSG, and presented in the appropriate appendix.

Table 3-8 is a summary of the number of valid models obtained, where a valid model is one that has at least one term significance with a p-value of less than 0.1, when performing the fitting of the model for the proposed CARF methodology for calculating GRCs. As the same results obtained for FSC 2320, none of these models are valid.

Table 3-8. Number of Valid Models in CARF FSG Regression (GRC)

Model Described	**Number of Valid Models Generated from Total**	**Total Number of Models with Data Available for Analysis**
Original GRC LA	0	28
Original GRC LS	0	36
Original GRC MA	0	28
Original GRC MS	0	36

The results presented in this section are the results obtained in performing the research for this thesis. While a full effort was made to replicate the exact procedure employed in the source code provided in the JMP file, the same exact resulting values of the calculations were not obtained. The obtained values point to inconsistent models with less desirable regression fits and where no models show validity. The effects of invalid regression models observed in obtaining CRC values are further noticed when obtaining GRC values.

C. ORDINARY LEAST SQUARES (OLS) FSC AND FSG REGRESSION

In this section, because we were unable to recreate the CRCs and GRCs using GLM, we construct corresponding regression models using Ordinary Least Squares. The results obtained under this approach are a major improvement in terms of model performance and number of CRCs and GRCs generated. The F-statistics obtained and the overall p-values observed, on some of the CRC and GRC regressions, are of a more acceptable statistical significance for the numeric predictors used. When the OLS regression fits are subjected to the same threshold as the GLM regressions, an F-statistic lower than 0.1 and at least one of the regression terms with a p-value of less than 0.1, we observe that, in some cases these fits become valid for the different levels and phases of conflict. We also observe that some of these better-behaved models make a more efficient use of the sparse historical data available, although such is not always the case.

1. OLS FSC Regression

For the OLS FSC regression, we use the same example of FSC 2320 as is used for the GLM regressed FSC CARF (CRC) methodology. Better-behaved models, showing consistency in the numeric predictors used and statistical significance in the terms' p-values, are observed. The results of this are presented in Table 3-9 for FSC ECC_LA, Table 3-10 for FSC ECC_LS, Table 3-11 for FSC ECC_MA, and Table 3-12 for FSC ECC_MS. Each table shows the resulting p-values for each of the terms used in the OLS regression and the estimate value, the standard error resulted, and the *t* value, for each coefficient. All of these OLS regression samples for FSC 2320 result in valid models. Although the resulting p-values for the interaction term AAO_TOTAL*BEST_COST remain above the significance threshold of 0.1, the rest of the terms for the OLS regressed example FSC 2320 remain at significant p-values well below 0.1.

Table 3-9. OLS fit for CARF FSC 2320 for Y=ECC_LA

OLS REGRESSED CARF FSC LA				**FSC 2320**
Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(> | t |)**
Intercept	0.065	0.005	12.28	4.13e-20
AAO_TOTAL	–5.61e-7	2.17e-7	–2.58	0.0115
BEST_COST	–6.39e-8	2.43e-8	–2.62	0.0102
AAO_TOTAL*BEST_COST	1.53e-12	1.11e-12	1.37	0.1734

Table 3-10. OLS fit for CARF FSC 2320 for Y=ECC_LS

OLS REGRESSED CARF FSC LS				**FSC 2320**
Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(> | t |)**
Intercept	0.006	0.0008	7.51	7.20e-11
AAO_TOTAL	–7.08e-8	3.37e-8	–2.09	0.0390
BEST_COST	–1.06e-8	3.77e-9	–2.81	0.0061
AAO_TOTAL*BEST_COST	2.47e-13	1.73e-13	1.43	0.1560

Table 3-11. OLS fit for CARF FSC 2320 for Y=ECC_MA

OLS REGRESSED CARF FSC MA				FSC 2320
Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(> | t |)**
Intercept	0.074	0.005	12.87	3.39e-21
AAO_TOTAL	–6.34e-7	2.37e-7	–2.66	0.0092
BEST_COST	–7.94e-8	2.66e-8	–2.98	0.0037
AAO_TOTAL*BEST_COST	1.65e-12	1.22e-12	1.35	0.1790

Table 3-12. OLS fit for CARF FSC 2320 for Y=ECC_MS

OLS REGRESSED CARF FSC MS				FSC 2320
Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(> | t |)**
Intercept	0.015	0.001	8.69	3.51e-13
AAO_TOTAL	–1.43e-7	7.44e-8	–1.93	0.0568
BEST_COST	–2.62e-8	8.32e-9	–3.14	0.0023
AAO_TOTAL*BEST_COST	3.71e-13	3.81e-13	0.97	0.3335

As a result of the OLS modeling methodology, we obtain more valid models when compared to the proposed methodology approach. Table 3-13 is a summary of the number of valid models obtained, where, once again, a valid model is one that has at least one term significance with a p-value of less than 0.1, when performing the fitting of the model using a OLS regression method for calculating CARF FSCs.

Table 3-13. Number of Valid Models in OLS CRC CARF Regression

Model Described	Total Number of Models with Data Available for Analysis	Number of Valid Models Generated from Total	Total Number of TAMCN (CEC 1) CRCs Generated by OLS	Number of CARF CRCs Generated by GLM
OLS CRC LA	58	13	270	190
OLS CRC LS	87	16	496	197
OLS CRC MA	58	14	369	2
OLS CRC MS	87	16	586	3

In this table, the “Total Number of Models with Data Available for Analysis” column, expressed by the applicable CRC level and phase of conflict, represents the overall number of models observed to have all the data necessary to perform the analysis. The “Number of Valid Models Generated from Total” refers to the results of the validity comparison for term significance from the previous column totals. The “Total number of

TAMCN (CEC 1) CRCs Generated" provides the total possible number of TAMCNs that have been assigned a CRC value, only for CEC 1, and only for that level and phase of conflict. The last column is provided for the purpose of comparison to the original totals obtained from the file provided for the study of this thesis as part of a draft version of a originally proposed CARF methodology and refers to the total CARF values assigned. This same description applies to the rest of these similar tables presented in this section. OLS produces a substantially higher number of CRCs than does GLM, especially for MA and MS levels.

2. OLS FSG Regression

Better-behaved models showing consistency in the numeric predictors used and statistical significance in the terms' p-values are observed when we follow an OLS-regressed FSG CARF methodology (GRC) for the same example of FSG 12, as is used in the GLM-regressed GRC methodology. The results of these are presented in Tables 3–14 for FSG ECC_LA, 3–15 for FSG ECC_LS, 3–16 for FSG ECC_MA, and 3–17 for FSG ECC_MS. Each table shows the resulting p-values, the estimate value, the standard error resulted, and the *t* value for each coefficient. All the models for FSG 12 are valid, showing an improvement for term significance p-values, with most of them remaining below 0.1. A few exceptions are observed, as is the case of the value for the AAO_TOTAL and the interaction term, when the response variable is ECC_LS and ECC_MS. Nevertheless, the rest of the regressed model fits remain valid based on our previously established validity threshold.

Table 3-14. OLS CARF FSG 12 fit for Y=ECC_LA

OLS REGRESSED CARF FSG LA				**FSG 12**
Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(> | t |)**
Intercept	-.0003	0.0009	-0.430	0.6891
AAO_TOTAL	1.37e-7	5.16e-8	2.65	0.0565
BEST_COST	1.48e-7	5.98e-8	2.48	0.0679
AAO_TOTAL*BEST_COST	-5.67e-12	2.54e-12	-2.23	0.0893

Table 3-15. OLS CARF FSG 12 fit for Y=ECC_LS

OLS REGRESSED CARF FSG LS				FSG 12
Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(> | t |)**
Intercept	0.0003	0.0001	3.21	0.0092
AAO_TOTAL	-.43e-12	4.34e-10	-0.01	0.9848
BEST_COST	7.26e-8	1.65e-8	4.39	0.0013
AAO_TOTAL*BEST_COST	2.32e-13	4.24e-13	0.54	0.5965

Table 3-16. OLS CARF FSG 12 fit for Y=ECC_MA

OLS REGRESSED CARF FSG MA				FSG 12
Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(> | t |)**
Intercept	0.00008	0.0007	0.107	0.9193
AAO_TOTAL	1.70e-7	4.31e-8	3.95	0.0167
BEST_COST	4.19e-7	4.99e-8	8.39	0.0011
AAO_TOTAL*BEST_COST	-.14e-12	2.12e-12	-2.89	0.0443

Table 3-17. OLS CARF FSG 12 fit for Y=ECC_MS

OLS REGRESSED CARF FSG MS				FSG 12
Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(> | t |)**
Intercept	0.001	0.0003	3.25	0.0086
AAO_TOTAL	-.80e-10	1.24e-9	-0.70	0.4951
BEST_COST	3.36e-7	4.73e-8	7.10	0.00003
AAO_TOTAL*BEST_COST	1.16e-12	1.21e-12	0.95	0.3602

Table 3-18 is a summary of the number of valid models obtained, where a valid model is one that has at least one term significance with a p-value of less than 0.1, when performing the fit using OLS methodology for GRCs.

Table 3-18. Number of Valid Models in OLS GRC CARF Regression

Model Described	Total Number of Models with Data Available for Analysis	Number of Valid Models Generated from Total	Total Number of TAMCN (CEC 1) GRCs Generated by OLS	Number of CARF GRCs Generated by GLM
OLS GRC LA	28	11	398	46
OLS GRC LS	36	11	406	51
OLS GRC MA	28	11	707	59
OLS GRC MS	36	10	605	65

3. OLS Aggregate FSG Regression (by ECC and FSC)

Though the draft version of CARF methodology mentions that every GRC regression model is built on the results of the ECCs obtained and the CRC regressions, we are unable to identify specific traces that could show this approach was performed. With that in mind, we test the result that can be obtained by following the specific assignment algorithm in the decision flow map, presented in Figure 1-1, for a proposed FY2011 CARF assignment methodology. In doing so, the previously calculated ECCs and the obtained FSC CARFs (CRCs), for all levels and phases of conflict, are provided as inputs to the constructed model used to obtain FSG CARFs (GRCs). The results of such an approach under an OLS methodology, using the previously employed example of FSG 12, are presented in Tables 3-19 for CARF FSG LA, 3–20 for CARF FSG LS, 3–21 for CARF FSG MA, and 3-22 for CARF FSG MS. In addition, each table shows the resulting p-values, the estimate value, the standard error resulted, and the *t* value for each coefficient. With the exception of the regressed fit when the response variables of ECC_LS and ECC_MS are used, the rest are very stable and valid models. Even with the explicit exceptions, at least one term—in both cases, the interaction term—remains well below a p-value of 0.1, making the overall regression fit good, thus suggesting a valid model.

Table 3-19. OLS CARF FSG 12 LA (created by ECCs and FSC inputs)

OLS REGRESSED CARF FSG LA (Using ECCs and FSCs)				**FSG 12**
Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(> | t |)**
Intercept	-.038	0.0166	-2.29	0.1050
AAO_TOTAL	0.00006	0.00001	5.06	0.0148
BEST_COST	2.02e-7	3.83e-8	5.28	0.0132
AAO_TOTAL*BEST_COST	-7.62e-10	1.33e-10	-5.70	0.0106

Table 3-20. OLS CARF FSG 12 LS (created by ECCs and FSC inputs)

OLS REGRESSED CARF FSG LS (Using ECCs and FSCs)				**FSG 12**
Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(> | t |)**
Intercept	0.004	0.0006	6.17	0.0034
AAO_TOTAL	-.32e-9	4.73e-9	-0.49	0.6494
BEST_COST	1.01e-9	6.70e-10	1.51	0.2050
AAO_TOTAL*BEST_COST	-8.33e-12	1.93e-12	-4.31	0.0125

Table 3-21. OLS CARF FSG 12 MA (created by ECCs and FSC inputs)

OLS REGRESSED CARF FSG MA (Using ECCs and FSCs)				FSG 12
Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(> | t |)**
Intercept	-.04	0.018	-2.14	0.1210
AAO_TOTAL	0.00007	0.00001	4.95	0.0157
BEST_COST	2.23e-7	4.31e-8	5.18	0.0139
AAO_TOTAL*BEST_COST	-8.44e-10	1.50e-10	-5.61	0.0111

Table 3-22. OLS CARF FSG 12 MS (created by ECCs and FSC inputs)

OLS REGRESSED CARF FSG MS (Using ECCs and FSCs)				FSG 12
Coefficients	**Estimate**	**Std. Error**	**t value**	**Pr(> | t |)**
Intercept	0.01	0.001	5.53	0.0052
AAO_TOTAL	-.94e-9	1.34e-8	-0.29	0.7831
BEST_COST	2.45e-9	1.89e-9	1.29	0.2652
AAO_TOTAL*BEST_COST	-2.11e-11	5.47e-12	-3.85	0.0182

Table 3-23 is a summary of the number of valid models obtained when aggregating ECCs and CRCs to calculate GRCs, identified in the table as OLS AGGREGATE GRC XX, where a valid model is one that has at least one term significance with a p-value of less than 0.1.

Table 3-23. Number of Valid Models in CARF FSG OLS Regression (created with ECC and CRC input) Methodology

Model Described	Total Number of Models with Data Available for Analysis	Number of Valid Models Generated from Total	Total Number of TAMCN (CEC 1) GRCs Generated	Number of CARF GRCs Assigned by GLM
OLS AGGREGATED GRC LA	55	16	540	46
OLS AGGREGATED GRC LS	60	14	414	51
OLS AGGREGATED GRC MA	55	12	308	59
OLS AGGREGATED GRC MS	60	16	708	65

Looking at the number of resulting models of the aggregated OLS GRC methodology, we see an increase obtained from making use of the available calculated values of ECCs and CRCs. Both the number of models with data available for analysis, followed by the number of valid models obtained, provide the resulting increase in overall TAMCNs able to have a calculated CARF CRC model. The last column in

Tables 3-22 and 3-23 present the results of the originally reported GRC models from Table 2-3. The increase, obtained when following an OLS and an OLS aggregated approach in usable models, is indicative of an improvement and of another possible approach in which further research could be invested. It is also prudent to emphasize here that the results presented for OLS regression have been of an exploratory nature and have not been fully validated by this thesis. Furthermore, no other analytical parameters than the ones mentioned here were specifically traced or studied with the intention to validate the before-mentioned procedure. Nevertheless, in finding the results depicted in this section, the need for further research into more robust and less labor-intensive practices and methodologies has become evident.

D. CROSS-VALIDATION APPROACH TO IDENTIFY DATA SUFFICIENCY FOR EFFECTIVE ANALYSIS

In this section, we cross validate a small sample of our regression models. The primary intent is to evaluate the performance of the models, but we also hope to gain some insight in determining how sensitive the models are to gaps in the data.

In every trial, we withhold different percentages of the available TAMCNs data. With this, we can run the regression models and compare the accuracy of that individual model to produce resulting values similar to those from the originally regressed values of the data withheld. In every case, the percentages of data withheld are 20%, 15%, and 10%. The examples we use are FSCs 2320 and 5820 and FSG 23. These FSCs and FSG are personally chosen because of their amount of available CEC 1 TAMCNs with available data and because of their primary importance, as rolling stock and communications equipment, to the operating forces.

Every example that follows employs the OLS-regressed procedure and presents the resulting summary of fit of that particular model, in every level and phase of conflict, having the specific percentage of data withheld and the explanation of the total numbers used. Also presented are the observed results' distributions for that specific percentage of data withheld and the resulting predicted values. A table at the end of every example compiles these resulting numbers and identifies which ones remained inside the 90-percentile confidence interval, which was explained in Section A of this chapter. For the FSG example, only results for conflict level and phases LA and MS are presented with the intention of just emphasizing the most relevant results.

1. Example Using FSC 2320, Wheeled Trucks and Truck Tractors

Using the previous example of FSC 2320, where a total of 181 TAMCNs are available and we have originally 84 ECC_LAs, ECC_LSs, ECC_MAs, and ECC_MSs, we perform a cross validation in order to identify symptoms the regression would show when randomly withholding 20% (17 of the 84 observations withheld) of the available data. Figure 3-7 shows the resulting values for the OLS regression fit for ECC_LA.

Response ECC_LA FSC=2320

Summary of Fit

RSquare	0.175789
RSquare Adj	0.136541
Root Mean Square Error	0.023393
Mean of Response	0.042482
Observations (or Sum Wgts)	67

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	0.00735324	0.002451	4.4789
Error	63	0.03447662	0.000547	**Prob > F**
C. Total	66	0.04182986		0.0065*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.0489275	0.007166	6.83	<.0001*
AAO_TOTAL	-1.758e-7	8.455e-8	-2.08	0.0416*
BEST_COST	-8.666e-9	2.526e-8	-0.34	0.7327
(AAO_TOTAL-26534.1)*(BEST_COST-221217)	1.476e-12	1.06e-12	1.39	0.1688

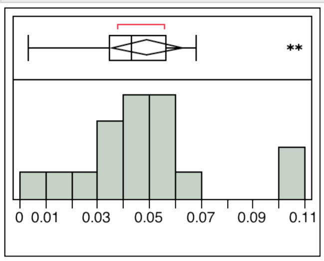
Figure 3-7. OLS Fit for CARF FSC 2320 with Y=ECC_LA When 20% of TAMCN Data is Withheld.

In this example, there is only one numeric predictor term with a p-value of less than 0.1 and one that closely approaches that threshold. These are sufficient enough results to observe this regression fit as valid based on our previously established model validity criteria of at least one term’s p-value being less than 0.1.

The distribution of the withheld data for comparison of the results of the cross validation procedure is presented in Figure 3-8. The distribution of the original ECC_LAs shows a wide range (0.0032, 0.1077), while the distribution for the predicted CRC_LAs, with 20% data randomly withheld, shows a very much-restricted range, (0.0404, 0.0626). This, in turn, translates not into predicted values remaining inside the wide range of original values, but actually failing to remain inside the previously calculated confidence interval, as presented in Table 3-24.

Distributions

ECC_LA Original



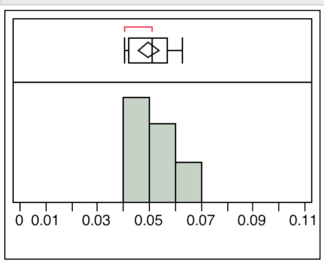
Quantiles

100.0%	maximum	0.10775
99.5%		0.10775
97.5%		0.10775
90.0%		0.1055
75.0%	quartile	0.05632
50.0%	median	0.04288
25.0%	quartile	0.03456
10.0%		0.01505
2.5%		0.00328
0.5%		0.00328
0.0%	minimum	0.00328

Moments

Mean	0.0490712
Std Dev	0.0264895
Std Err Mean	0.0064246
Upper 95% Mean	0.0626909
Lower 95% Mean	0.0354516
N	17

Predicted CRC_LA



Quantiles

100.0%	maximum	0.06262
99.5%		0.06262
97.5%		0.06262
90.0%		0.06128
75.0%	quartile	0.05691
50.0%	median	0.05115
25.0%	quartile	0.04179
10.0%		0.04045
2.5%		0.04045
0.5%		0.04045
0.0%	minimum	0.04045

Moments

Mean	0.0496847
Std Dev	0.0079132
Std Err Mean	0.0019192
Upper 95% Mean	0.0537533
Lower 95% Mean	0.0456161
N	17

Figure 3-8. Comparison Distributions of Original ECC_LA and Predicted CRC_LA for the 20% Withheld.

Table 3-24. Predicted CRC_LA and Original ECC_LA comparison with CI, for the 20% withheld

TAMCN	ECC_LA Original	Predicted CRC_LA	Interval Lower Bound	Interval Upper Bound	Predicted CRC_LA in CI
D00337KA	0.0033	0.0543	0.0031	0.0037	No
D01987K	0.0429	0.0404	0.0420	0.0439	No
D01987K	0.0429	0.0404	0.0421	0.0437	No
D01987KA	0.0429	0.0512	0.0422	0.0438	No
D02097K	0.1049	0.0416	0.1040	0.1058	No
D08777K	0.0314	0.0512	0.0292	0.0373	No
D08817K	0.0569	0.0530	0.0550	0.0597	No
D08867K	0.0180	0.0419	0.0161	0.0204	No
D10627K	0.0377	0.0469	0.0362	0.0397	No
D10627K	0.0377	0.0426	0.0362	0.0397	No
D10727K	0.1078	0.0527	0.1016	0.1144	No
D10737K	0.0289	0.0440	0.0282	0.0302	No
D11257K	0.0481	0.0626	0.0452	0.0508	No
D11587KA	0.0678	0.0609	0.0671	0.0683	No
D11597K	0.0558	0.0601	0.0556	0.0560	No
D11597K	0.0558	0.0595	0.0556	0.0560	No
D12137K	0.0516	0.0412	0.0493	0.0541	No

In Table 3-24, we can observe the obtained predicted CRC values for the LA, only for the 20% data randomly withheld, as compared to the originally obtained ECC values. The lower and upper interval columns are from the calculated confidence intervals obtained and presented in Section A of this chapter. The last column of this table confirms if the obtained predicted value falls inside that confidence interval. In this case, there are no predicted CRC_LAs that meet this criteria. For FSC 2320 with an LA level and phase of conflict, even missing just 20% of TAMCNs with available data (i.e., 17 of 84) renders the regressed CRC values unreliable.

The rest of these figures and tables have been omitted here, but can be found in Appendix H. The compiled results have been properly tabulated and are discussed at the end of this section.

When we withhold roughly 15% (12 of the 84 TAMCNs) and 10% (8 of the 84 TAMCNs) of the available data for the same FSC 2320, the resulting summary of fits for ECC_LA show valid regressions. Nevertheless, even when only withholding 10% of the data, the results do not improve. None of the obtained predicted CRC values in both cases remain inside the determined confidence interval. For this level and phase of conflict, the regressed CRC values are likely marginally reliable.

Following the same cross-validation approach on FSC 2320, with a 20% of TAMCN data randomly withheld, for ECC_LS we can observe that the regression fit remains valid when we consider that the cross-effect term has a resulting p-value of less than 0.1, as shown in Figure 3-9.

Response ECC_LS FSC=2320

Summary of Fit

RSquare	0.082866
RSquare Adj	0.039193
Root Mean Square Error	0.002742
Mean of Response	0.002633
Observations (or Sum Wgts)	67

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	0.00004281	0.000014	1.8974
Error	63	0.00047383	7.521e-6	**Prob > F**
C. Total	66	0.00051664		0.1391

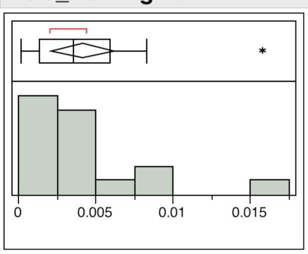
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.0026331	0.00084	3.13	0.0026*
AAO_TOTAL	-2.818e-9	9.912e-9	-0.28	0.7771
BEST_COST	2.477e-10	2.961e-9	0.08	0.9336
(AAO_TOTAL-26534.1)*(BEST_COST-221217)	2.16e-13	1.24e-13	1.74	0.0871

Figure 3-9. OLS Fit for CARF FSC 2320 with Y=ECC_LS When 20% of TAMCN Data is Withheld.

Distributions

ECC_LS Original



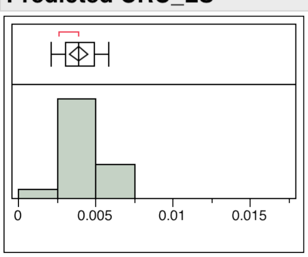
Quantiles

100.0%	maximum	0.0158
99.5%		0.0158
97.5%		0.0158
90.0%		0.00976
75.0%	quartile	0.00592
50.0%	median	0.00353
25.0%	quartile	0.00134
10.0%		0.00016
2.5%		0.00016
0.5%		0.00016
0.0%	minimum	0.00016

Moments

Mean	0.0041095
Std Dev	0.003959
Std Err Mean	0.0009602
Upper 95% Mean	0.0061451
Lower 95% Mean	0.002074
N	17

Predicted CRC_LS



Quantiles

100.0%	maximum	0.00585
99.5%		0.00585
97.5%		0.00585
90.0%		0.00562
75.0%	quartile	0.00486
50.0%	median	0.00386
25.0%	quartile	0.00307
10.0%		0.00254
2.5%		0.00213
0.5%		0.00213
0.0%	minimum	0.00213

Moments

Mean	0.0039051
Std Dev	0.0011164
Std Err Mean	0.0002708
Upper 95% Mean	0.0044791
Lower 95% Mean	0.003331
N	17

Figure 3-10. Comparison of Distributions of Original ECC_LS and Predicted CRC_LS for the 20% Withheld.

The distributions presented in Figure 3-10 for the original ECC_LSs and the predicted CRC_LSs show similar results than those of the distributions presented for ECC_LA and the predicted CRC_LA, but for this level and phase of conflict, when we compare the resulting predicted CRC values to the previously established confidence intervals, we are able to identify that seven of the 17 TAMCNs (Table 3-25) with data that were randomly selected and withheld were predicted values that remained inside the mentioned interval. This suggests that, in this level and phase of conflict, and possibly because the available data is less sparse here, we are still able to consider valuable the reliance on some of the predicted values.

Table 3-25. Predicted CRC_LS and Original ECC_LS Comparison with CI, for the 20% Withheld

TAMCN	ECC_LS Original	Predicted CRC_LS	Interval Lower Bound	Interval Upper Bound	Predicted CRC_LS in CI
D00337KA	0.0002	0.0044	0.0001	0.0006	No
D01987K	0.0035	0.0032	0.0027	0.0046	Yes
D01987K	0.0035	0.0032	0.0027	0.0044	Yes
D01987KA	0.0035	0.0039	0.0028	0.0044	Yes
D02097K	0.0044	0.0031	0.0035	0.0052	No
D08777K	0.0082	0.0039	0.0060	0.0142	No
D08817K	0.0079	0.0044	0.0061	0.0108	No
D08867K	0.0024	0.0030	0.0004	0.0047	Yes
D10627K	0.0020	0.0034	0.0005	0.0040	Yes
D10627K	0.0020	0.0026	0.0005	0.0040	Yes
D10727K	0.0158	0.0041	0.0097	0.0225	No
D10737K	0.0007	0.0028	0.0006	0.0020	No
D11257K	0.0074	0.0059	0.0045	0.0102	Yes
D11587KA	0.0042	0.0056	0.0035	0.0046	No
D11597K	0.0002	0.0054	0.0001	0.0004	No
D11597K	0.0002	0.0053	0.0001	0.0004	No
D12137K	0.0037	0.0021	0.0014	0.0062	No

The rest of these figures and tables have been omitted here, but can be found in Appendix H. The compiled results have been properly tabulated and are discussed at the end of this section.

When randomly withholding 15% and 10% of the data on FSC 2320 for ECC_LS, the regression fits also remain valid. We also observe that as we withhold less data, in this case and for this level and phase of conflict, the numbers of predicted CRC values that remain inside the confidence interval improve. This suggests that most of the predicted CRC values are still reliable.

Similar results are observed when randomly withholding the same depicted amounts of data throughout the rest of this analysis for ECC_MAs and ECC_MSs. The rest of the results for FSC 2320, at every level and phase of conflict and with the different amount of TAMCN data withheld, are compiled in Table 3-26. Though we have established a flexible 90% confidence interval, only one model, CRC_LS, is able to show predicted values inside this interval at a mere 75%. As well, it is evident that CRC_LA shows no acceptable performance and does not maintain any predicted values inside the bootstrapped confidence interval developed.

Table 3-26. Cross Validation Compiled Results for FSC 2320

FSC 2320	**20% Data Withheld (17 of 84)**		**15% Data Withheld (12 of 84)**		**10% Data Withheld (8 of 84)**	
	Number of CRCs in CI	**Percent in CI**	**Number of CRCs in CI**	**Percent in CI**	**Number of CRCs in CI**	**Percent in CI**
LA	0 of 17	0%	0 of 12	0%	1 of 9	0%
LS	7 of 17	41%	6 of 12	50%	6 of 9	75%
MA	3 of 17	18%	2 of 12	17%	3 of 9	25%
MS	8 of 17	47%	6 of 12	50%	6 of 9	50%

When comparing the overall results of the cross-validation for FSC 2320, we can observe that the assault phases for both levels of conflict are the ones with the least resiliency and least reliability for predicted CRC values. As far as the low and medium levels, in the sustainment phases, we see that even when we withhold 10% of the data the model has trouble generating estimates that are inside the bootstrapped CIs.

2. Example Using FSG 23, Motorized Vehicles

For the cross-validation approach on an FSG, we used FSG 23, Motor Vehicles, Trailers, and Cycles, with a total of 324 TAMCNs CEC 1 available and broken down in FSCs, as shown in Figure 3-11.

	FSC					
FSG	2310	2320	2330	2340	2350	2355
23	7	181	60	4	16	56

Figure 3-11. Number of TAMCNs in FSG 23 by FSC.

From the original data, of these 324 TAMCNs, 180 each have ECC_LAs, ECC_LSs, ECC_MAs, and ECC_MSs.

The resulting figures and tables for this cross validation have also been omitted here, but can be found in Appendix I. The compiled results have been properly tabulated and are discussed at the end of this section.

The effects observed when randomly withholding 20% (36 of the 180 observations withheld) of the available data and performing an OLS regression with the response variable as ECC_LA, show that the regression fit remains valid, but when we compare the resulting predicted CRC values to the previously established confidence intervals, only 2 of the 36 TAMCNs remained inside the mentioned interval. This suggests that, in this level and phase of conflict, and for this FSG, only some of these regressed predicted values could be considered reliable.

The same results are observed when randomly withholding only 15% (27 of 180) of the data for the ECC_LA. The regression fit and none of the resulting predicted CRC values remain inside the mentioned interval. In withholding only 10% (18 of 180) of the data for ECC_LA, the regression fit remains valid with only 2 of the 18 predicted CRC values remaining inside the mentioned interval.

The rest of the results for FSG 23, at every level and phase of conflict and with the different amount of TAMCN data withheld, are compiled in Table 3-27.

Table 3-27. Cross Validation Compiled Results for FSG 23

FSG 23*	20% Data Withheld (36 of 180)		15% Data Withheld (27 of 180)		10% Data Withheld (18 of 180)	
	Number of GRCs in CI	Percent in CI	Number of GRCs in CI	Percent in CI	Number of GRCs in CI	Percent in CI
LA	2 of 36	5%	0 of 27	0%	2 of 18	11%
MS	11 of 36	31%	8 of 27	30%	5 of 18	28%
* Only Conflict Levels LA and MS are represented in this table.						

We are able to identify a trend in which, even at 90% bootstrapped confidence intervals constructed from only 50 replications, predicted values rarely remain inside that interval. This should remain as a cause for concern, since it is a clear indication of the lack of robustness we are detecting.

When comparing the overall results of the cross validation for FSG 23, we can observe an FSG that is very susceptible to changes in the data. For the low-level assault phase, it is observed that any missing data would create a substantial detrimental effect on the minimum amount of reliability currently obtained on this FSG's predicted CRC values. For the MS level, missing any more than 20% of the data could create a further rippling effect on the reliability of the predicted CRC values.

3. Example Using FSC 5820, Radio Communications Equipment

Another example of cross validation is used with FSC 5820, Radio and Television Communications Equipment (except airborne), where a total of 171 TAMCNs CEC 1 are available and we have originally 87 TAMCNs with each, ECC_LSs and ECC_MSs, and 86 TAMCNs with each, ECC_LAs and ECC_MAs.

The resulting figures and tables for this cross validation have also been omitted here, but can be found in Appendix J. The compiled results have been properly tabulated and are discussed at the end of this section.

The effects observed when randomly withholding 20% (17 of the 87) of the available data and performing an OLS regression, with the response variable as ECC_LA, show that the regression fit is valid with all of the numeric predictor terms' resulting p-value far below 0.1. When we compare the resulting predicted CRC values to the previously established confidence intervals, we are able to identify that only one of the 87 TAMCNs, with data that were randomly selected and withheld, were predicted values that remained inside the mentioned interval.

By randomly withholding only 15% (13 of 87) and 10% (9 of 87) of the data for ECC_LA, the regression fits remain perfectly valid with all the regression terms at very low p-values of at most 0.0012. Nevertheless, in both cases, we do not see an improvement when we compare the resulting predicted CRC values to the previously established confidence intervals, since only one of the 87 TAMCNs remained inside the mentioned interval.

The effects observed when randomly withholding 20% (17 of the 87 withheld) of the available data and performing an OLS regression with the response variable as ECC_LS, show that the regression fit becomes invalid with all of the regression terms, hovering around 0.9. Comparing the resulting predicted CRC values to the previously established confidence intervals, 6 of the 17 TAMCNs were predicted values that remained inside the interval.

When we randomly withhold only 15% and 10% of the data for ECC_LS, the regression fits remain invalid and all of the regression terms obtain p-values around 0.8. Yet, when we compare the resulting predicted CRC values to the previously established confidence intervals, on average, 40% remained inside the mentioned interval.

Similar results are observed when randomly withholding the same depicted amounts of data throughout the rest of this analysis for ECC_MAs and ECC_MSs. The rest of the results for FSC 5820, at every level and phase of conflict and with the different amount of TAMCN data withheld, are compiled in Table 3-28. Also, as mentioned for FSC 2320, though we have established a flexible 90% confidence interval, there are only two models—in this case, CRC_LS and CRC_MS—that are able to show predicted values inside this interval, but only for 67% of the time. It is also evident that in the case of CRC_LA, though showing better results for FSC 5820 compared to the results of FSC 2320, the regression fit's performance is unfavorable and does not provide any predicted values inside the above-mentioned confidence interval.

Table 3-28. Cross Validation Compiled Results for FSC 5820

FSC 5820	20% Data Withheld (17 of 87)		15% Data Withheld (13 of 87)		10% Data Withheld (9 of 87)	
	Number of CRCs in CI	Percent in CI	Number of CRCs in CI	Percent in CI	Number of CRCs in CI	Percent in CI
LA	1 of 17	6%	1 of 13	8%	1 of 9	11%
LS	5 of 17	29%	4 of 13	31%	6 of 9	67%
MA	1 of 17	6%	3 of 13	23%	3 of 9	33%
MS	7 of 17	41%	7 of 13	54%	6 of 9	67%

When comparing the overall results of the cross validation for FSC 5820, we can observe an FSC that has more consistent results, based on the greater availability of historical data. Although the regression fits are not perfectly valid, with some resulting in overwhelmingly invalid fits, we can see that LA remains unchanged through the process of comparing percentages of data missing. We can assume this FSC, and level and phase of conflict, to be lacking enough data to provide a sufficiently reliable regression model and predicted CRCs.

The approach of gradually withholding data presented in this section, though labor-intensive, has the intention to demonstrate a method for exploring amount of data sufficiency. This is done in order to provide a means of identifying which amount of data would be necessary to replicate an efficient and valid model. In addition, from these few observations, it is evident that individual tests and studies seem to be necessary for every FSC and FSG when trying to pinpoint specific amounts of data required, if the intention is to obtain the most reliable and stable models for predicting CRCs and GRCs. We have also observed that every CRC and FSG reacts differently to the amount of data missing, not just because of the inherent equipment differences they are identified with, but also by the different levels and phases of conflict to which they apply. Improvements in consistency and accuracy in all types of data collected would be the overarching solution.

IV. CONCLUSIONS AND RECOMMENDATIONS

A. SUMMARY OF FINDINGS

A full effort was made to replicate the procedure employed in the source code provided in the JMP file, but the same exact resulting values of the calculations, as presented in an early version of a CARF study draft report, were not obtained. The results of our calculations point to inconsistent models with substantially less than desirable regression fits.

1. ECC Sensitivity

We generate 50 bootstrapped replications of the historic usage data to obtain a distribution of ECCs for those TAMNs with available usage data. We show that based on the individual level and phase of conflict, many ECCs are significantly sensitive to minimal changes in the data with which they are calculated. We find that 12 of low level ECCs and 140 of medium level ECCs are not significantly different from zero. The least sensitive was the ECC_LAs, where 82 of 611 showed high sensitivity, while the most sensitive was the ECC_MSs, with 357 of 514 being highly sensitive.

2. GLM and OLS Comparison

We were unable to replicate the GLM regressions outlined in an early version of a CARF study draft report. Our results expressed that the fit of these models did not provide the validity necessary to predict reliable CRC or GRC values. Term significance in every one of these models was less than favorable.

In comparison, an OLS approach had vast improvements in term significance and model validity. In most cases, we were able to obtain, on average, a 20% improvement in generating valid models across the levels and phases of conflict, which progressed into an increase in the number of CRCs and GRCs produced. For example, when observing CRCs for MSs, the increase goes from 3 to 586, and in GRCs for MAs, the increase goes from 59 to 707. No validation was performed in the entire OLS process. Employing OLS regressions is representative of mainly exploratory intentions. Yet, the results obtained emphasize the need for further methodology research.

B. RECOMMENDATIONS AND AREAS FOR FURTHER RESEARCH

We emphasize that accurate CARF calculations provide the planning flexibility to meet requirements of any conflict and operational plan. It is imperative to understand that CARFs are an indispensable tool in determining WRM stocks.

1. Bootstrapping

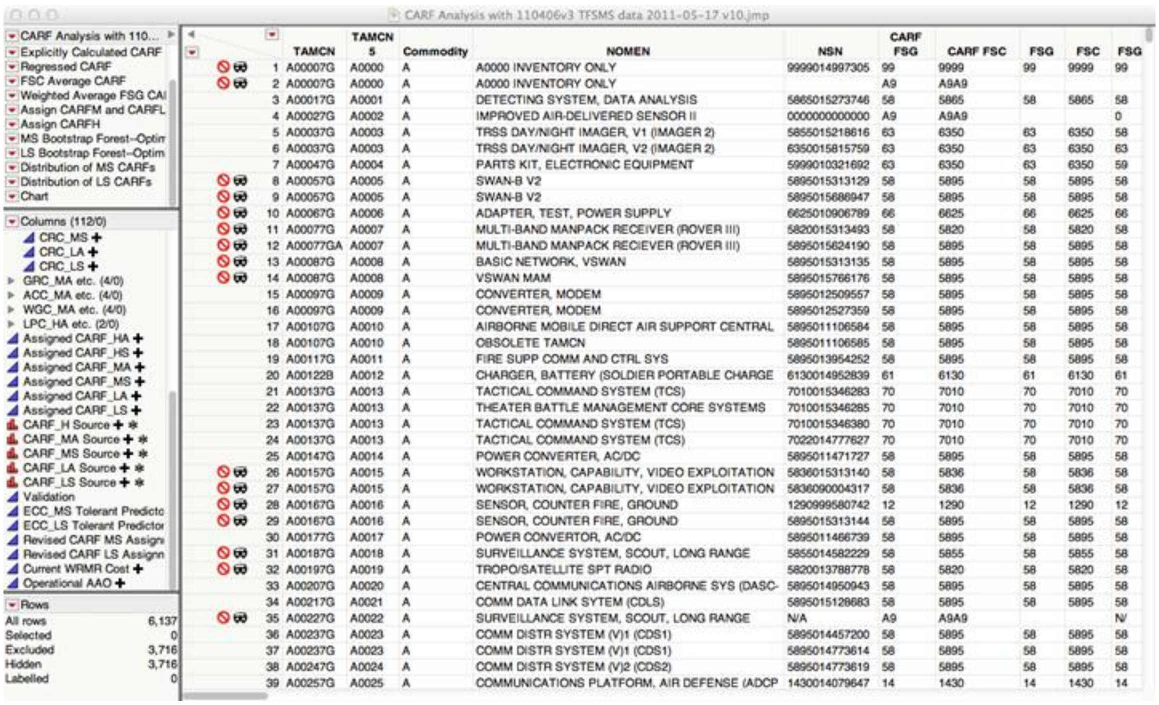
The bootstrapping approach and analysis was only performed over casualties and only on 50 replications. Further simulation could be performed following the same presented approach over casualties with more than 1,000 replications. This could yield a more fine-tuned method to further identify which parts of the data are more sensitive to greater fluctuations. In addition, distributions of CRCs and GRCs could be attained by performing that analysis on each bootstrapped replication.

2. Regression Analysis

Some of the regression analysis performed for this thesis was done within JMP in order to replicate the proposed procedures. Other regression analysis was performed in SAS statistical software, which is the case of the OLS results presented. We recommend performing a comprehensive validation of each of the regression models built, to include analyzing the residuals to determine normality, homoscedasticity, and level of autocorrelation.

APPENDIX A

Screen capture of the JMP file that contains both the data-table, as well as the scripts to perform most of the necessary calculations. The first 39 rows of 6,137 are shown.



	TAMCN	TAMCN 5	Commodity	NOMEN	NSN	CARF FSG	CARF FSC	FSG	FSC	FSG
1	A00007G	A0000	A	A0000 INVENTORY ONLY	9999014997305	99	9999	99	9999	99
2	A00007G	A0000	A	A0000 INVENTORY ONLY		A9	A9A9			
3	A00017G	A0001	A	DETECTING SYSTEM, DATA ANALYSIS	5865015273746	58	5865	58	5865	58
4	A00027G	A0002	A	IMPROVED AIR-DELIVERED SENSOR II	0000000000000	A9	A9A9			0
5	A00037G	A0003	A	TRSS DAY/NIGHT IMAGER, V1 (IMAGER 2)	5855015218616	63	6350	63	6350	58
6	A00037G	A0003	A	TRSS DAY/NIGHT IMAGER, V2 (IMAGER 2)	6350015815759	63	6350	63	6350	63
7	A00047G	A0004	A	PARTS KIT, ELECTRONIC EQUIPMENT	5999010321692	63	6350	63	6350	59
8	A00057G	A0005	A	SWAN-B V2	5895015313129	58	5895	58	5895	58
9	A00057G	A0005	A	SWAN-B V2	5895015686947	58	5895	58	5895	58
10	A00067G	A0006	A	ADAPTER, TEST, POWER SUPPLY	6625010906789	66	6625	66	6625	66
11	A00077G	A0007	A	MULTI-BAND MANPACK RECEIVER (ROVER III)	5820015313493	58	5820	58	5820	58
12	A00077GA	A0007	A	MULTI-BAND MANPACK RECIEVER (ROVER III)	5895015624190	58	5895	58	5895	58
13	A00087G	A0008	A	BASIC NETWORK, VSWAN	5895015313135	58	5895	58	5895	58
14	A00087G	A0008	A	VSWAN MAM	5895015766176	58	5895	58	5895	58
15	A00097G	A0009	A	CONVERTER, MODEM	5895012509557	58	5895	58	5895	58
16	A00097G	A0009	A	CONVERTER, MODEM	5895012527359	58	5895	58	5895	58
17	A00107G	A0010	A	AIRBORNE MOBILE DIRECT AIR SUPPORT CENTRAL	5895011106584	58	5895	58	5895	58
18	A00107G	A0010	A	OBSOLETE TAMCN	5895011106585	58	5895	58	5895	58
19	A00117G	A0011	A	FIRE SUPP COMM AND CTRL SYS	5895013954252	58	5895	58	5895	58
20	A00122B	A0012	A	CHARGER, BATTERY (SOLDIER PORTABLE CHARGE	6130014952839	61	6130	61	6130	61
21	A00137G	A0013	A	TACTICAL COMMAND SYSTEM (TCS)	7010015346283	70	7010	70	7010	70
22	A00137G	A0013	A	THEATER BATTLE MANAGEMENT CORE SYSTEMS	7010015346285	70	7010	70	7010	70
23	A00137G	A0013	A	TACTICAL COMMAND SYSTEM (TCS)	7010015346380	70	7010	70	7010	70
24	A00137G	A0013	A	TACTICAL COMMAND SYSTEM (TCS)	7022014777627	70	7010	70	7010	70
25	A00147G	A0014	A	POWER CONVERTER, AC/DC	5895011471727	58	5895	58	5895	58
26	A00157G	A0015	A	WORKSTATION, CAPABILITY, VIDEO EXPLOITATION	5836015313140	58	5836	58	5836	58
27	A00157G	A0015	A	WORKSTATION, CAPABILITY, VIDEO EXPLOITATION	5836090004317	58	5836	58	5836	58
28	A00167G	A0016	A	SENSOR, COUNTER FIRE, GROUND	1290999580742	12	1290	12	1290	12
29	A00167G	A0016	A	SENSOR, COUNTER FIRE, GROUND	5895015313144	58	5895	58	5895	58
30	A00177G	A0017	A	POWER CONVERTOR, AC/DC	5895011466739	58	5895	58	5895	58
31	A00187G	A0018	A	SURVEILLANCE SYSTEM, SCOUT, LONG RANGE	5855014582229	58	5855	58	5855	58
32	A00197G	A0019	A	TROPO/SATELLITE SPT RADIO	5820013788778	58	5820	58	5820	58
33	A00207G	A0020	A	CENTRAL COMMUNICATIONS AIRBORNE SYS (DASC-	5895014950943	58	5895	58	5895	58
34	A00217G	A0021	A	COMM DATA LINK SYTEM (CDLS)	5895015128683	58	5895	58	5895	58
35	A00227G	A0022	A	SURVEILLANCE SYSTEM, SCOUT, LONG RANGE	N/A	A9	A9A9			N/
36	A00237G	A0023	A	COMM DISTR SYSTEM (V)1 (CDS1)	5895014457200	58	5895	58	5895	58
37	A00237G	A0023	A	COMM DISTR SYSTEM (V)1 (CDS1)	5895014773614	58	5895	58	5895	58
38	A00247G	A0024	A	COMM DISTR SYSTEM (V)2 (CDS2)	5895014773619	58	5895	58	5895	58
39	A00257G	A0025	A	COMMUNICATIONS PLATFORM, AIR DEFENSE (ADCP	1430014079647	14	1430	14	1430	14

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APPENDIX B

Sample of Federal Supply Code (FSC) tables and classification list from http://www.dispositionservices.dla.mil/asset/fsclist.html.

Aircraft and Airframe Structural Components

1510 Aircraft, Fixed Wing
1520 Aircraft, Rotary Wing
1540 Gliders
1550 Drones
1560 Airframe Structural Components

Aircraft Components and Accessories

1610 Aircraft Propellers and Components
1615 Helicopter Rotor Blades, Drive Mechanisms and Components.
1620 Aircraft Landing Gear Components
1630 Aircraft Wheel and Brake Systems
1650 Aircraft Hydraulic, Vacuum, and De-icing System Components
1660 Aircraft Air Conditioning, Heating, and Pressurizing Equipment
1670 Parachutes; Aerial Pick Up, Delivery, Recovery Systems; and Cargo Tie Down Equipment
1680 Miscellaneous Aircraft Accessories and Components

Aircraft Launching, Landing, and Ground Handling Equipment

1710 Aircraft Landing Equipment.
1720 Aircraft Launching Equipment
1730 Aircraft Ground Servicing Equipment
1740 Airfield Specialized Trucks and Trailers
1810 Space Vehicles
1820 Space Vehicle Components
1830 Space Vehicle Remote Control Systems
1840 Space Vehicle Launchers
1850 Space Vehicle Handling and Servicing Equipment
1860 Space Survival Equipment

Ships, Small Craft, Pontoons, and Floating Docks

1905 Combat Ships and Landing Vessels
1910 Transport Vessels, Passenger and Troop

1915 Cargo and Tanker Vessels
1920 Fishing Vessels
1925 Special Service Vessels
1930 Barges and Lighters, Cargo
1935 Barges and Lighters, Special Purpose
1940 Small Craft
1945 Pontoons and Floating Docks
1950 Floating Drydocks

APPENDIX C

From Section A, Chapter III: FSCs with ECC_LSs and MSs that are outside of the sensitivity ratio criteria.

Table C-1. ECC_LSs and MSs that are outside of the sensitivity ratio criteria

FSC	TAMCN	NOMENCLATURE	Interval Lower Bound	Interval Upper Bound
B00157B	2330	Z BACKSCATTER RUGGEDIZED TRAILER (ZBRT)	0	0.0075
E08567K	2350	ASSAULT AMPHIBIOUS VEHICLE, RECOVERY	0	0.0486
E13787K	2350	RECOVERY VEHICLE, FT, HEAVY, W/EQUIP	0	0.0679
A21797G	5820	TERMINAL, RADIO, TROPOSCATTER, DIGITAL	0	0.0125
A21797G	5820	TERMINAL, RADIO, TROPOSCATTER, DIGITAL	0	0.0153
A21797G	5820	TERMINAL, RADIO, TROPOSCATTER, DIGITAL	0	0.0153
A23067G	2355	GROUND SENSOR SURVEILLANCE VEHICLE (GSSV)	0	0.0465
A04997G	5895	DIGITAL TECHNICAL CONTROL (DTC) FACILITY	0	0.0253
A04997G	5895	DIGITAL TECHNICAL CONTROL (DTC) FACILITY	0	0.0379
A21797G	5820	TERMINAL, RADIO, TROPOSCATTER, DIGITAL	0	0.0176
5820	A00757G	ARCHIVED TAMCN	0	0.0006
5895	A00917G	VIDEO SCOUT REMOTE VIDEO EXPLOITATION TERMINAL (RVET)	0	0.0006
5998	A00917G	VIDEO SCOUT REMOTE VIDEO EXPLOITATION TERMINAL (RVET)	0	0.0009
5998	A00917GA	VIDEO SCOUT REMOTE VIDEO EXPLOITATION TERMINAL (RVET)	0	0.0006
5895	A02857G	DISMTD DIGITAL AUTOMATED COMM TERMINAL (DDACT)	0	0.0004
5895	A04997G	DIGITAL TECHNICAL CONTROL (DTC) FACILITY	0	0.0048
5895	A04997G	DIGITAL TECHNICAL CONTROL (DTC) FACILITY	0	0.0072
5820	A09187G	RADIO SET, SATELLITE, TACTICAL, PORTABLE	0	0.0007
5820	A09187G	RADIO SET, SATELLITE, TACTICAL, PORTABLE	0	0.0009
5820	A09187GB	RADIO SET, SATELLITE, TACTICAL, PORTABLE	0	0.0009
5820	A09187GC	RADIO SET, SATELLITE, TACTICAL, PORTABLE	0	0.0009
5820	A09187GD	RADIO SET, SATELLITE, TACTICAL, PORTABLE	0	0.0009
6150	A09207G	SATELLITE COMMUNICATION	0	0.0008
5985	A13807G	ANTENNA, COMMUNICATION, TRLR MTD, LTWT	0	0.007
5985	A13807G	ANTENNA, COMMUNICATION, TRLR MTD, LTWT	0	0.0057
5985	A13807GA	ANTENNA, COMMUNICATION, TRLR MTD, LTWT	0	0.0094
5985	A13807GB	ANTENNA, COMMUNICATION, TRLR MTD, LTWT	0	0.0081
5895	A19587G	KIT, MAINT, ELECTRONIC EQUIPMENT	0	0.0053
5820	A20427G	RADIO SET, HIGH FREQUENCY, MANPACK	0	0.0001
5820	A20427G	RADIO SET, HIGH FREQUENCY, MANPACK	0	0.0001
5820	A20427GA	RADIO SET, HIGH FREQUENCY, MANPACK	0	0.0001
5820	A21717G	RADIO SET, VEHICULAR	0	0.0022
5820	A21717GI	RADIO SET, VEHICULAR	0	0.0015
5820	A21717GK	RADIO SET, VEHICULAR	0	0.0022

FSC	TAMCN	NOMENCLATURE	Interval Lower Bound	Interval Upper Bound
5820	A21717GL	RADIO SET, VEHICULAR	0	0.0025
5820	A21797G	TERMINAL, RADIO, TROPOSCATTER, DIGITAL	0	0.0024
5820	A21797G	TERMINAL, RADIO, TROPOSCATTER, DIGITAL	0	0.0022
5820	A21797G	TERMINAL, RADIO, TROPOSCATTER, DIGITAL	0	0.0027
5820	A21797G	TERMINAL, RADIO, TROPOSCATTER, DIGITAL	0	0.0027
5820	A21797G	TERMINAL, RADIO, TROPOSCATTER, DIGITAL	0	0.0019
2355	A23067G	GROUND SENSOR SURVEILLANCE VEHICLE (GSSV)	0	0.0098
2355	A23067G	SENSOR SYSTEM, MONITOR, MOBILE	0	0.0089
5411	A23362B	SHELTER, 20FT, EMI, MAINT COMPLEX	0	0.001
5411	A23382B	SHELTER, 10FT, RIGID, MAINT COMPLEX	0	0.0009
5805	A25057G	SWITCHBOARD, TELEPHONE, AUTOMATIC	0	0.0019
5895	A25357G	DATA NETWORK, TACTICAL (GATEWAY)	0	0.0079
5895	A25357G	DATA NETWORK, TACTICAL (GATEWAY)	0	0.0088
5895	A28087G	TEST SET, OPTICAL COMMUNICATIONS	0	0.0028
1550	A32527G	UAV SYSTEM, DRAGON EYE	0	0.001
1550	A32527G	UAV SYSTEM, RAVEN	0	0.0008
6625	A70057G	ANLYZER, SPECTRUM	0	0.0002
6625	A70057G	ANLYZER, SPECTRUM	0	0.0002
6625	A70057G	ANLYZER, SPECTRUM	0	0.0002
6625	A70057G	ANLYZER, SPECTRUM	0	0.0002
6625	A70057G	ANLYZER, SPECTRUM	0	0.0001
6625	A70057GA	ANLYZER, SPECTRUM	0	0.0002
6625	A70097G	ANALYZER, SPECTRUM, HAND HELD, CREW	0	0.0007
6625	A70097G	ANALYZER, SPECTRUM, HAND HELD	0	0.0007
6625	A70257G	COUNTER, ELECTRONIC	0	0.0093
6625	A70257G	COUNTER, ELECTRONIC	0	0.0102
6625	A70257G	COUNTER, ELECTRONIC	0	0.0114
6625	A70257G	20 GHZ CW FREQUENCY COUNTER	0	0.0063
	A70377G	OSCILLOSCOPE	0	0.0088
6930	A70467G	GENERATOR, SIGNAL	0	0.0036
6930	A70467G	GENERATOR, SIGNAL	0	0.004
6930	A70467G	40 GHZ SIGNAL GENERATOR	0	0.004
6930	A70527G	1 GHZ SIGNAL GENERATOR	0	0.0011
6930	A70597G	SOIL RESISTIVITY TESTER	0	0.0004
6930	A70847G	LOCAL AREA NETWORK TEST SET	0	0.0019
6930	A70847GA	ANALYZER, NETWORK	0	0.0021
6625	A70867G	OPTICAL TIME DOMAIN REFLECTOMETER (OTDR)	0	0.001
6625	A70867G	OPTICAL TIME DOMAIN REFLECTOMETER (OTDR)	0	0.0014
6625	A70867G	OTDR	0	0.0016
5180	A79002E	ELECTRONIC TOOL KIT	0	0.0001
5180	A79107G	TOOL KIT, FIBER OPTIC, GP	0	0.0016
5180	A79107G	GENERAL PURPOSE FIBER OPTIC TOOL KIT	0	0.0016
5895	A79557G	MICRO MINIATURE REPAIR STATION (PACE KIT)	0	0.003
5895	A79557G	MICRO MINIATURE REPAIR STATION (PACE KIT)	0	0.0034
6080	A79657G	KIT, CONNECTOR, FIBER OPTIC	0	0.0231
5810	A80447G	LIMITED MAINT SPARE PARTS KIT	0	0.0034
2330	B00157B	Z BACKSCATTER RUGGEDIZED TRAILER (ZBRT)	0	0.0012
2330	B00157B	VAN, Z BACKSCATTER	0	0.0014

FSC	TAMCN	NOMENCLATURE	Interval Lower Bound	Interval Upper Bound
4210	B00457B	EXPEDITIONARY FIRE SUPPRESSION SYSTEM	0	0.0064
3810	B04467B	AIR MOBILE CRANE, RT, HYDRAULIC, LT (SLEP)	0	0.0024
3810	B04467B	AIR MOBILE CRANE, RT, HYDRAULIC, LT (SLEP)	0	0.0027
3810	B04467B	AIR MOBILE CRANE, RT, HYDRAULIC, LT (SLEP)	0	0.0019
8110	B05717B	DRUM, FABRIC, COLLAPSIBLE, 500 GAL. CAP.	0	0.0012
8110	B05717B	DRUM, FABRIC, COLLAPSIBLE, 500 GAL. CAP.	0	0.0011
2430	B05897B	EXCAVATOR, COMBAT	0	0.003
2430	B05897B	M9 ARMORED COMBAT EARTHMOVER	0	0.0037
4210	B06257B	COMPRESSED AIR-FOAM SYSTEM, MOBILE	0	0.0042
4930	B06757B	TACTICAL AIRFIELD FUEL DISPENSING SYSTEM (TAFDS) (FIRESTONE)	0	0.0101
4930	B06757B	TACTICAL AIRFIELD FUEL DISPENSING SYSTEM (TAFDS) (FIRESTONE)	0	0.0101
4930	B11357B	REFUELING SYSTEM, EXPEDIENT, HELO	0	0.0173
1055	B12987B	KIT, LAUNCH, LINE CHARGE, TRLR-MTD	0	0.0015
1055	B12987B	KIT, LAUNCH, LINE CHARGE, TRLR-MTD	0	0.0013
4320	B15707B	EXPEDIENT REFUELING SYSTEM (ERS)	0	0.0014
4320	B15707B	EXPEDIENT REFUELING SYSTEM (ERS)	0	0.0014
5180	B22602E	TOOL KIT, PIONEER, ENGR SQUAD	0	0.0007
5180	B22602E	PIONEER KIT (SQD)	0	0.0009
2430	B24627B	TRACTOR, FT, MEDIUM (CATERPILLAR)	0	0.0039
6630	B26307B	ANALYSIS SET, QUALITY, PURIFICATION, WATER	0	0.0081
6630	B26307B	ANALYSIS SET, QUALITY, PURIFICATION, WATER	0	0.0091
6630	B26307B	ANALYSIS SET, QUALITY, PURIFICATION, WATER	0	0.0081
3431	B26857B	WELDING SHOP, MARINE CORPS TACTICAL	0	0.0032
6625	B70012G	ANALYZER, ELECTRICAL PULSE	0	0.0204
6625	B70012G	ANALYZER, ELECTRICAL PULSE	0	0.0181
6625	B70012G	3-PHASE POWER ANALYZER	0	0.0163
5855	C00042E	ULTRA HIGH INTENSITY MINIATURE ILLUMINATION SYSTEM	0	0.0001
3530	C60702T	SEWING MACHINE, INDUSTRIAL, HVY DUTY, LEATHER	0	0.0075
3530	C60812T	SEWING MACHINE, ZIGZAG, MED DUTY	0	0.0102
3530	C60812T	SEWING MACHINE, ZIGZAG, MED DUTY	0	0.0102
3530	C61012T	SINGLE NEEDLE KIT-MEDIUM WEIGHT	0	0.0057
4910	C70167B	DYNAMOMETER, RUN-IN, 1800HP	0	0.0459
4940	C70252B	TEST SET, HYDRAULIC, IN-LINE	0	0.0062
4940	C70252B	TEST SET, HYDRAULIC, IN-LINE	0	0.0041
4940	C70252B	TEST SET, HYDRAULIC, IN-LINE	0	0.0062
4910	C70722B	TEST STAND, GEN/STARTER AND ALTERNATOR	0	0.0011

25	Scaled Deviance	5	0	0	orig_fsg_la
25	Pearson Chi-Square	5	1.94933E-31	3.89866E-32	orig_fsg_la
25	Scaled Pearson X2	5	1.94933E-31	3.89866E-32	orig_fsg_la
25	Log Likelihood		-0.80257565		orig_fsg_la
34	Deviance	0	0		orig_fsg_la
34	Scaled Deviance	0	0		orig_fsg_la
34	Pearson Chi-Square	0	2.23489E-33		orig_fsg_la
34	Scaled Pearson X2	0	2.23489E-33		orig_fsg_la

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